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RESEARCH PAPER

Spatial Transferability of a Daily Activity Type and Duration MDCEV Model

Nohekhan, A.[1]**, Samimi, A.**[2*] **and Zahedian, S.**[1]

[1] Ph.D. Candidate, Department of Civil and Environmental Engineering, University of Maryland, Maryland, United States of America.
[2] Associate Professor, Department of Civil Engineering, Sharif University of Technology, Tehran, Iran.

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ABSTRACT: This paper explores the transferability of the Multiple Discrete-Continuous Extreme Value (MDCEV) model for activity type and duration using various transfer methods and sample sizes. This study employs the data of travel demand studies in two major cities, Shiraz and Mashhad in Iran. The model is first developed for Shiraz and then transferred to Mashhad. The adopted transfer methods are transfer scaling, Bayesian updating, combined transfer estimation, and joint context estimation. Aggregate and disaggregate transfer measures are adopted to examine the transferred models' general prediction and policy predictability. The results indicate the joint context estimation method's superiority in terms of estimation and policy prediction powers. The available massive data to the authors enabled measuring the value of sample size in this study. The sample size sensitivity analysis revealed a decrease in the marginal gain of the transferred model's performance as the sample size increases. Remarkably, the transferred model outperforms even the locally estimated model when 1) advanced transfer techniques are applied (i.e., the combined transfer estimation and the joint context estimation), and 2) the application context sample size is large enough (i.e., more than 30 percent).

Keywords: Bayesian Updating, Combined Transfer Estimation, Joint Context Estimation, MDCEV Model, Model Transfer, Spatial Transferability, Transfer Scaling.

1. Introduction

The spatial and temporal transfer of travel demand models could undercut obstacles that impede many cities from conducting transportation studies (Ziemke et al., 2015; Lefebvre-Ropars et al., 2017). Since the 70s, several studies have explored traditional travel demand models' transferability with promising results (Salem and Nurul Habib, 2015). However, the transferability of advanced Activity-Based Models (ABM) is only discussed in a handful of studies (Yasmin et al., 2015), necessitating more research on this topic. Remarkably, the transferability of individual-level activity generation/time-use models is of interest due to the required high-resolution and disaggregated data for model development, an extremely costly

[*] Corresponding author E-mail: asamimi@sharif.edu

and labor-intensive data to collect (Xiong et al., 2020). Although the application of deep learning models has taken pace in Civil Engineering (Karimaee Tabarestani and Zarrati, 2015; Barkhordari and Entezari Zarch, 2015) and, in particular, Transportation Engineering (Zahedian et al., 2020; Nohekhan et al., 2021) to capture the complex interdependencies between the input attributes, the black box structure of these models is the primary obstacle in providing the necessary insights for decision-makers. Therefore, econometrics models capable of delivering such insight while producing accurate estimates for complex behaviors are essential. The MDCEV model, a budget-based approach, is increasingly adopted to model individual-level activity patterns (Wafa et al., 2015) and incorporated in several activity-based travel model systems (Bhat, 2018). Such a growing application of MDCEV models motivated this research to investigate these models' spatial transferability regarding the required sample data and experiment with various well-known transfer methods.

The transferability of transportation model components is widely studied using different methods with varying success levels. Notably, the transferability of activity generation model components is evidenced to be more feasible than those for other travel choices (Bowman and Bradley, 2017) due to the low dependency of individuals' daily activity on the built environment (Sikder and Pinjari, 2013). Arentze et al. (2002), for instance, applied the naïve transfer method and found "substantial evidence for the spatial transferability of Albatross, except for transport mode". Further, Nowrouzian and Srinavasan (2012) used the same method to transfer tour generation models and argued that conventional aggregate transfer metrics are insufficient to ensure acceptable performance for policy assessments. Bowman et al. (2014) adopted a joint context estimation approach and considered two different sample sizes to transfer 14 model components of DaySim. They determined that the transferred model estimated with a large sample size outperforms the locally estimated model (Bowman et al., 2014).

Yasmin et al. (2015) evaluated the transferability of TASHA (Travel Activity Scheduler for Household Agents), an activity-based model developed for the Greater Toronto Area, Canada, to the Island of Montreal, Canada. The authors explored the spatial transferability of the modeled activity attributes, including frequency, start time, duration, and distance, using a naïve transfer approach. The results illustrated the transferability of the models for work, school, and return to home activities. However, due to differences in behaviors, the transfer models performed poorly on other activities, and a re-estimation step was recommended.

Bowman and Bradley (2017) used the same data and approach to test the transferability of 12 model components of DaySim. They tested similarities in three data segments, namely within-state, similar trip distance, and similar density. They identified "state grouping" as the best criterion, followed by density and trip distance grouping. Tang et al. (2018) explored the spatial transferability of a Neural Network (NN) mode choice model using the naïve transfer and a NN model adaptation method. They train five NN models for five regions of Washington DC and Baltimore and found that while the naïve transfer method is applicable in areas with high similarities, the proposed NN model adaptation method is more suitable for regions with significant differences.

In a more recent study, the spatial transferability of FEATHERS, an ABM model developed for Flanders, Belgium, to Ho Chi Minh City, Vietnam, is explored (Linh et al., 2019). The study found some transferability levels using the naïve method; however, it recommended a recalibration step for all sub-models. In analyzing the potential impacts of the connected and automated transportation technology on travel behavior, Shabanpour et al. (2019) proposed a transferable framework developed on a small geographic area to generate disaggregate travel data in other regions.

The transferability of MDCEV models has specific gaps, despite the relatively rich literature of model transfer in general. Sikder and Pinjari (2013) introduced one of the earliest papers that studied MDCEV transferability. They used simple transfer methods, namely naïve transfer and constants updating, and argued that the ability to predict aggregate patterns does not necessarily imply good transferability. They determined that updating constants can improve predictions relative to observed patterns. However, this method does not guarantee improved model performance in response to changes in demographic characteristics (Sikder and Pinjari, 2013). Wafa et al. (2015) proposed a latent segmentation approach to endogenously determine appropriate criteria for clustering regions in estimating MDCEV models. This approach had better performance than traditional exogenous identification methods.

The shortcoming in most of these studies is that they have used basic transfer methods. Besides, the effects of sample size and transfer methods on the MDCEV model's predictability have been largely neglected. A summary of the published ABM transferability studies is presented in Table 1 to obtain a broad overview of the literature gaps. This paper fills the gaps by applying four widely-used transfer methods to examine the spatial transferability of the MDCEV models in two major cities, Shiraz and Mashhad, in Iran. The data used for estimating the MDCEV model and its transferability exploration is the household travel behavior surveys conducted in these two cities. The survey in Mashhad is conducted in 1994 and Shiraz in 1999. While these data are old, the study's main contribution is from the methodological aspect of transferability analysis of the MDCEV model, which is independent of the data collection date. At the time of the survey, Mashhad had roughly 1.8 million and Shiraz 1.2 million residents. In terms of public transportation, both cities at the time of data collection had an extensive network of fixed-route bus lines but no metro lines. Each of these cities has a distinct Central Business District (CBD) comprising mixed land use, with urban neighborhoods situated around the CBD. The present study compares alternative methods of model transfer and analyzes sample size effects on the estimation outcome. The selected transfer procedures are transfer scaling, Bayesian updating, combined transfer estimation, and joint context estimation, each of which is described in detail in the following section.

The structure of the remainder of the paper is as follows. In the second section, the methodology of the study is presented. This section contains a description of the MDCEV model, transfer methods, and transferability metrics. In the third section, the data of the study is introduced and described. This description presents the sociodemographic characteristics and the activity types and time allocations in Mashhad and Shiraz. In the fourth section, the results of estimating the MDCEV model in each region are briefly presented, followed by a detailed description of the transferred models' performance and transferability metrics analysis for each transfer method and various sample sizes of the application context data. In the last section, the findings are summarized and discussed to elaborate on the study's conclusions. Besides, the contributions of this research and recommendations for future studies in transferability analysis are presented in this section.

2. Methodology

This section first presents an overview of the MDCEV model formulation, followed by introducing and discussing the applied transfer methods. Finally, aggregate and disaggregate transferability assessment metrics for comparing the transferred models' performance are introduced, allowing for a more robust comparison of the transfer methods.

2.1. MDCEV Model

Several travel demand decisions, including activity type and duration, require a simultaneous choice of multiple alternatives (Shamshiripour and Samimi, 2019). Traditional discrete and discrete-continuous models cannot be effectively adopted in such cases, as these models are applicable when only one alternative among a set of alternatives is chosen (Bhat, 2018; Mondal and Bhat, 2021). Unlike the traditional models, the MDCEV model allows choosing different choices with different quantities besides observing diminishing marginal returns with an increase in any specific alternative's consumption (Pinjari and Bhat, 2010). The MDCEV model estimated in this study adopts the same utility form presented, in Eq. (1), as suggested by Bhat (2008):

$$U(x) = exp(\varepsilon_1).ln(t_1) + \sum_{k=2}^{K} \gamma_k [exp(\beta^T z_k + \varepsilon_k)].\ln(\frac{t_k}{\gamma_k} + 1) \quad (1)$$

where the first term relates to the utility of allocating time to the activity in which every individual participates (in-home activity in our study), also known as the "outside good", γ_k: is the translation parameter, t_k: is the corresponding allocated time to activity k ($t_k \geq 0$ for all k), β: is a coefficient vector related to activity k, z_k: is a vector of attributes, and ε_k: captures the unobserved characteristics that impact the baseline utility for activity purpose k.

Table 1. Summary of activity-based model transferability literature

Author(s)	Year	ABM studied	Location	Transfer methods	Assessment metrics
Arentze et al.	2002	ALBATROSS	Netherlands	Naïve transfer	Transferred model's aggregate and disaggregate level prediction ability
Nowrouzian and Srinavasan	2012	Original	Florida, USA	Naïve transfer	Elasticity comparisons, Root mean square error between predicted and observed shares
Bowman et al.	2014	DaySim	California, Florida, USA	Joint context estimation (using pooled data of different regions)	Transferability test statistic, t-statistics of difference variables capturing differences in parameters between counties
Sikder and Pinjari	2013	MDCEV	California, Florida, USA	Naïve transfer, Constants updating approach	Transferability test statistic, Root mean square error, Transfer index, Relative aggregate transfer error
Yasmin et al.	2015	TASHA	Toronto, Montreal, Canada	No transfer method implemented	K-S test, Comparison of differences
Wafa et al.	2015	MDCEV	California, Florida, USA	Latent segmentation-based approach	Bayesian information criterion
Bowman and Bradley	2017	Daysim	California, Texas, Florida, and New York, USA	No transfer method implemented	Transferability index, tests of coefficient differences
Tang et al.	2018	NN model	Washington DC, Baltimore, USA	No transfer method implemented	Hit ratio, overall prediction accuracy, mean absolute relative error, root mean square error, relative aggregate transfer error
Linh et al.	2019	FEATHERS	Flanders, Belgium; Ho Chi Minh City, Vietnam	No transfer method implemented	Comparison of differences
Shabanpour et al.	2019	POLARIS	Chicago, Illinois, USA	No transfer method implemented	Comparison of differences

Each person is assumed to maximize his/her utility according to a time budget, formulated as $\sum_{k=1}^{K} t_k = T$, where T: is the time budget (i.e., 24 hours). Eq. (2) illustrates the probability expression for the time allocation to the first M of the K activities (assuming the first alternative as the "outside good") (Bhat, 2008):

$$P(t_1^*, t_2^*, t_3^*, \dots, t_M^*, 0,0, \dots,0) = \frac{1}{\sigma^{M-1}}\left[\prod_{i=1}^{M} c_i\right]\left[\sum_{i=1}^{M} \frac{1}{c_i}\right]\left[\frac{\prod_{i=1}^{M} t^{V_i/\sigma}}{\left(\sum_{k=1}^{K} t^{V_k/\sigma}\right)^M}\right](M-1)! \quad (2)$$

where σ: is the scale parameter and c_i: is calculated as follows:

$$c_i = \left(\frac{1}{t_i^* + \gamma_i}\right); \quad 1 \le i \le M \quad (3)$$

To predict the activity pattern for a given person, Pinjari and Bhat (2010) presented a procedure for predicting the amount of time spent on each activity. This method is used in this study to predict the total amount of time spent for each activity type. Interested readers may refer to Bhat (2008, 2018) and Pinjari and Bhat (2010) for a more detailed description of the MDCEV model structure and the forecasting algorithm.

2.2. Transfer Methods

The spatial model transfer is built upon the notion that the estimated parameters using the data of a region (termed as estimation context) can provide valuable information for estimating the model parameters in another area (termed as application context). There are several levels of model transferability classified as follows Karasmaa (2003):

- The behavioral assertion (e.g., utility maximization),
- Mathematical model class (e.g., a logit formulation),
- Model specifications (e.g., a linear utility function), and
- Model coefficients.

Depending on the type and quality of the data, a model transfer is achievable in at least four approaches: 1) Transfer scaling, 2) Bayesian updating, 3) Combined transfer estimation, and 4) Joint context estimation (Rossi and Bhat, 2014). The following section briefly discusses these well-known model transfer methods.

2.2.1. Transfer Scaling

The primary assumption in transfer scaling is that the model structure is the same across application and estimation contexts. Karasmaa (2003) discussed the four following techniques to apply the transfer scaling approach:

- Naïve transfer: The simplest transfer method is naïve transfer, in which the estimated model is exactly used for the application context (Atherton and Ben-Akiva, 1976).

- Adjusting constant terms: Aggregate data can be utilized to correct the constant terms; therefore, the model imitates existing aggregate data. Therefore, all the model coefficients except for the constant terms are accepted (Atherton and Ben-Akiva, 1976). In this situation, the general utility function of the application context model can be written as follows (Karasmaa, 2003):

$$V_j = C_j + \beta'_i X_i \quad (4)$$

where V_j: is the vector of the general utility function in the application context, C_j: is the vector of constants in the application context, β_i: is the matrix of coefficients in the estimation context, and X_i: is the vector of variables in estimation context.

- Estimating new constants and scale: All or some of the application context's utility function parameters are scaled, in this case. Further, alternative-specific constants are estimated using a sample from application context data assuming that the utility function's remaining parameters are directly transferable from the estimation context (Atherton and Ben-Akiva, 1976). The transfer method formulates the utility function according to Eq. (5) as follows

(Karasmaa, 2003):

$$V_j = C_j + \rho\beta'_i X_i \quad (5)$$

where ρ: is the vector of scale factors for each set of explanatory variables to be scaled.

- Estimating the application context model: A small sample is used, assuming that it represents the choice behavior. In this method, all the estimation context model variables appear in the application context model, and the parameters are estimated solely based on the application context data. This method is identical to transfer scaling if all the coefficients are re-scaled (Karasmaa, 2003).

2.2.2. Bayesian Updating

The primary assumption in the Bayesian updating method is the similarity of individuals' behavior in the estimation and application contexts. This assumption enables combining the parameters estimated from an application context sample data with the estimation context parameter values to update the parameters using a classical Bayesian analysis (Karasmaa, 2003). In its essence, Bayesian updating optimally combines the coefficients estimated on the application and estimation contexts separately, considering the coefficients' estimated variances (Atherton and Ben-Akiva, 1976). This procedure calculates a weighted average of the coefficients in which weights are equal to the inverse of the estimated coefficients' variance, as presented in Eq. (6). It is noteworthy that the weighted average technique is applicable when the coefficient estimates are normally distributed.

$$\hat{\beta}_{transferred} = (\Sigma_i^{-1} + \Sigma_j^{-1})^{-1}(\Sigma_i^{-1}\hat{\beta}_i + \Sigma_j^{-1}\hat{\beta}_j) \quad (6)$$

where $\hat{\beta}_i$ and $\hat{\beta}_j$: are the estimated parameter vectors in the estimation and application contexts, respectively; Σ_i and Σ_j: are the variance-covariance matrices of estimated parameters for the estimation and application contexts, respectively.

2.2.3. Combined Transfer Estimation

This method is a generalization of Bayesian updating and incorporates transfer scaling (Karasmaa, 2003). The assumption of identical behavioral model parameters between the estimation and application context in Bayesian updating could be quite different from reality in the case of distinct geographical regions where actual differences between parameters of the estimated models might exist (Karasmaa, 2003). The combined transfer estimation method is based on the mean squares error criterion, extending the Bayesian procedure to explicitly account for the transfer bias. The transferred model parameters are determined using Eq. (7):

$$\hat{\beta}_{transferred} = [(\Sigma_i + \Delta\Delta')^{-1} + \Sigma_j^{-1}]^{-1}[(\Sigma_i + \Delta\Delta')^{-1}\hat{\beta}_i + \Sigma_j^{-1}\hat{\beta}_j] \quad (7)$$

where Δ: is the transfer bias approximated by the estimated bias: $\Delta \approx \hat{\beta}_j - \hat{\beta}_i$.

2.2.4. Joint Context Estimation

The Joint context estimation method involves estimating a new joint model using both the estimation context and application context data (Karasmaa, 2003). The basic idea of merging datasets from different regions is to modify the random variation in the datasets' utility functions (Ben-Akiva and Morikawa, 1990). The following notations are used to develop the joint context estimation technique:

r: superscript denoting context (= 1 for estimation context set; = 2 for application context), ψ_k^r: baseline utility of alternative k in context r, λ_k^r: deterministic baseline utility of alternative k in context r, ε_k^r: random component of the baseline utility for alternative k in context r, ζ: vector of utility function parameters assumed to be constant across the contexts, s_k^r: vector of explanatory variables for alternative k

shared with context r, σ^r: vector of utility function parameters that are assumed to be specific for context r, τ_k^r: vector of context-specific explanatory variables for alternative k within context r, μ: utility function scale for alternative k in context 2. For the sake of simplicity, the context superscript is not written; μ: is the ratio of the context 2 scale to the constant scale 1 for alternative k with unidentifiable absolute values for each of these scales.

The systematic baseline utility for each activity in the two contexts considering the definitions above is as follows:

$$\psi_k^1 = exp(\sigma^{1T}\tau_k^1 + \zeta^T s_k^1 + \varepsilon_k^1) \quad \forall k; 1 \leq k \leq K \tag{8}$$

$$\psi_k^2 = exp(\sigma^{2T}\tau_k^2 + \zeta^T s_k^2 + \varepsilon_k^2) \quad \forall k; 1 \leq k \leq K \tag{9}$$

Therefore, the systematic utility function for each person in each context is as follows:

$$U^1(x) = \sum_{k=1}^{K} \gamma_k^1 \psi_k^1 \ln\left(\frac{x_k}{\gamma_k^1} + 1\right) = \sum_{k=1}^{K} \gamma_k^1 exp(\sigma^{1T}\tau_k^1 + \zeta^T s_k^1 + \varepsilon_k^1) \ln\left(\frac{x_k}{\gamma_k^1} + 1\right) \tag{10}$$

$$U^2(x) = \sum_{k=1}^{K} \gamma_k^2 \psi_k^2 \ln\left(\frac{x_k}{\gamma_k^2} + 1\right) = \sum_{k=1}^{K} \gamma_k^2\, exp\big(\sigma^{2T}\tau_k^2 + \zeta^T s_k^2 + \varepsilon_k^2\big) \ln\left(\frac{x_k}{\gamma_k^2} + 1\right) \tag{11}$$

The MDCEV model assumes that the unobserved effects are Independently and Identically Distributed (IID) across different alternatives (Bhat, 2008). The combined transfer estimation method assumes that random terms have IID properties within each of the datasets. Nevertheless, no general reason is to assume that ε_k^1 and ε_k^2 have an identical distribution, or to be more specific, have equal variances, as the effect of unobserved factors may be different for the two datasets. To equalize the variances of ε_k^1 and ε_k^2, the utility functions in the second context are scaled by μ (Badoe and Miller, 1995):

$$\mu^2 = \frac{var(\varepsilon_1)}{var(\varepsilon_2)} \tag{12}$$

If the random components in each dataset follow the IID Gumbel distribution, and the second context's baseline utility is powered by μ, the combined data follows the IID Gumbel distribution (Karasmaa, 2003). Thus, the application context's baseline utility function will be:

$$(\psi_k^2)^\mu = [exp(\sigma^{2T}\tau_k^2 + \zeta^T s_k^2 + \varepsilon_k^2)]^\mu = exp(\mu\sigma^{2T}\tau_k^2 + \mu\zeta^T s_k^2 + \varepsilon_k^1) \tag{13}$$

It is now possible to estimate the model using both contexts' merged data as the error terms variance in both contexts are equal (Train, 2009). Here $\mu = e^{\delta D}$, where D: is a dummy variable equal to one, if the observation belongs to the application context and zero otherwise. Thus, μ: equals to one for the estimation context and e^{δ} for the application context. This exponential form also guarantees the positivity of the utility function scale. Table 2 summarizes the assumptions made in each of the above transfer methods. As can be seen, the joint context estimation method is a more generic method than the others since it relaxes the transferability of the model specification assumption in addition to model coefficients transferability assumption relaxation of others.

2.3. Transferability Metrics

An empirical assessment of transferability is essential to evaluate the performance of the transferred models. This study implicitly assumes that the underlying behavioral assertion and mathematical model structure are transferable. The appropriate transferability metrics considering this assumption are presented in Table 3 (Sikder et al., 2013). The first measure, the t-test of individual parameters, shows whether the model is transferrable without any modifications between the two contexts. Next, the transferability test statistic is a log-likelihood-based test used to examine whether the transferred model's predictions are equal to the locally estimated model's predictions in the application context. The other log-likelihood-based measures are ρ_T^2 and Transfer index. The ρ_T^2 describes the goodness-of-fit of the transferred model in the application context, relative to a reference model such as a constants-only model (Atherton and Ben-Akiva, 1976; Abdelwahab, 1991).

The transfer index measures the transferred model's goodness-of-fit relative to the same model specification estimated in the application context (Koppelman and Wilmot, 1982). Among the aggregate-level prediction metrics, the relative error measure compares the estimated and observed share of selected choices (Koppelman and Wilmot, 1982). The Root-mean-square error measures a weighted average of the relative error measure based on each choice's observation share (Abdelwahab, 1991).

Table 2. Comparison between the assumptions of transfer methods

Transfer method		**Transferability**			
		Behavioural	**Mathematical**	**Specifications**	**Coefficients**
Transfer scaling	Naïve transfer	✓	✓	✓	✓
	Adjusting constant terms	✓	✓	✓	
	Estimating new constants and scale	✓	✓	✓	
	Estimating the application context model	✓	✓		
Bayesian updating		✓	✓	✓	
Combined transfer estimation		✓	✓	✓	
Joint context estimation		✓	✓		

Table 3. Summary of transferability assessment metrics

Test type	**Test name**	**Expression**
Statistical test of equivalence of individual parameter parameters	t-tests of Individual Parameter Equivalence	$\frac{(\beta_i)-(\beta_j)}{\sqrt{SE(\beta_i)^2+SE(\beta_j)^2}}$
Statistical test of equivalence of parameters	Transferability Test Statistic (TTS)	$-2[LL_i(\beta_j) - LL_i(\beta_i)]$
Measure of disaggregate-level predictive ability	Transfer rho-square (ρ_T^2)	$1-\frac{LL_i(\beta_j)}{LL_i(C_i)}$
	Transfer Index (TI)	$\frac{LL_i(\beta_j)-LL_i(C_i)}{LL_i(\beta_i)-LL_i(C_i)}$
Measure of aggregate-level predictive ability	Relative Error Measure (REM)	$(PS_k-OS_k)/OS_k$
	Root-Mean-Square Error (RMSE)	$(\frac{\sum_k PS_k \times REM_k^2}{\sum_k PS_k})^{1/2}$
	Relative Aggregate Transfer Error (RATE)	$\frac{RMSE_i(\beta_j)}{RMSE_i(\beta_i)}$
	Aggregate Prediction Statistic (APS)	$\sum_k \frac{(PS_k-OS_k)^2}{PS_k}$

Notation: *LL*: stands for log-likelihood value, and *β*: for a vector of parameters, while *i*, *j*: are subscripts for locally estimated and transferred models, respectively. $LL_i(\beta_i)$: is log-likelihood of the local model applied to application context data, $LL_i(\beta_j)$: is log-likelihood of the transferred model applied to application context data, $LL_i(C_i)$: log-likelihood of a constants only model for application context data, OS_k and PS_k: are the observed and predicted shares, respectively, for alternative *k*.

The relative aggregate transfer error is used to determine the transferred model's aggregate-level predictive performance relative to a model estimated using the application context data (Abdelwahab, 1991; Koppelman and Wilmot, 1982). Finally, the aggregate prediction statistic tests the null hypothesis, where the observed alternative shares are generated by the transferred model in the application context (Abdelwahab, 1991). A more detailed discussion of the pros and cons of different assessment metrics are made elsewhere (Sikder and Pinjari, 2013).

3. Data

This study's data sources are extracted from the comprehensive transportation master plans of Mashhad, Iran (1994) as the application context and Shiraz, Iran (1999) as the estimation context. The selection of this dataset was primarily due to the following reasons:

- The same research team conducted both studies and implemented quite similar data collection methods;
- The entire data with tens of thousands of observations were available to the authors, thus allowing for testing the out-of-sample predictive power of the transferred model without data limitations;
- A wide range of context data sample sizes, from 1 to 50 percent, was available to evaluate the transferred model's performance sensitivity; and
- Methodological evaluation of the MDCEV model transferability, the primary purpose and contribution of the current study, is regardless of the data collection date.

The surveys collected detailed information on all out-of-home activities undertaken by the respondents. At the time, Mashhad and Shiraz, respectively, had almost 1.8 and 1.2 million inhabitants.

The sample sizes were 73,304 (4.1 percent of the population) in Mashhad and 51,212 (4.3 percent of the population) in Shiraz. These studies did not collect the activities of children younger than six years of age. Further, respondents residing out of the city limits were omitted from the database. This yields to 61,036 individuals in Mashhad and 42,969 individuals in Shiraz. The activities of the respondents were classified into ten groups as follows: 1) In-home, 2) Work, 3) Education, 4) Shopping, 5) Personal business, 6) Health care, 7) Visiting relatives, 8) Recreation, 9) Travel, and 10) Other activities.

Table 4 summarizes several statistics on the demographics, activity participation, and time allocation patterns in each region. Figure 1 illustrates the cumulative time allocations for each of the ten activity types among individuals from both contexts based on their gender. Each point represents the percentage of individuals who participated in the activity more than the point's duration. For example, in part (a) of this figure, 37 percent of males and 68 percent of Shiraz females spent more than 1,200 minutes on in-home activities.

4. Results and Discussions

4.1. Original Models

In the first analysis step, two MDCEV activity patterns (type and duration) models are estimated for Shiraz and Mashhad, with 80 percent of the individuals randomly selected from each dataset. The 20 percent remaining observations of each city were reserved to determine the transferred models' out-of-sample prediction accuracy. The estimating and evaluation of the MDCEV model and later transferring the models is implemented in the STATA software (StataCorp, 2015, Stata Statistical Software: Release 14, College Station, TX: StataCorp LP). While complete model estimation results are provided in the appendix (Tables A1 and A2), Table 5 summarizes these results. These results indicate that the models' performance in their estimation region is comparable. The takeaway from the coefficient estimates, which can be justified by looking at the

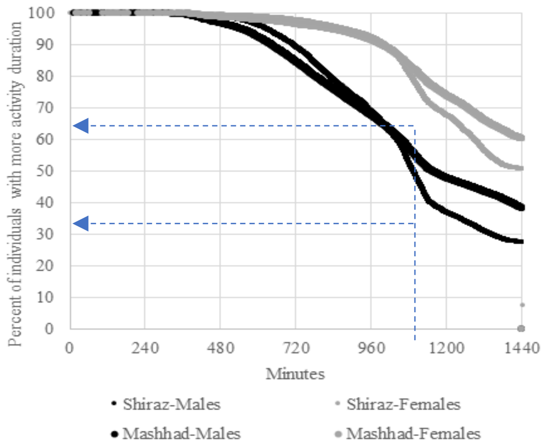
Tables A1 and A2 of the appendix, is that individual and household characteristics have rational signs and are similar in both models. For instance, senior citizens tend to participate more in healthcare and in-home activities than younger people, and individuals in smaller families spend more time shopping. The same happens with the geographical zones' specifications. As the proportion of commercial areas in the residence zone increases, individuals tend to participate more in shopping activities. The detailed results of performing t-tests between individual models' parameters are presented in the appendix (Table A3). This test revealed that almost 80 percent of the coefficients are statistically different across the two contexts. Thus, each of the models can hardly be used in another context. However, using a context's model in another context does not necessarily result in wrong predictions since a combination of various parameters determines the model's prediction accuracy.

4.2. Transferred Models Assessment Metrics

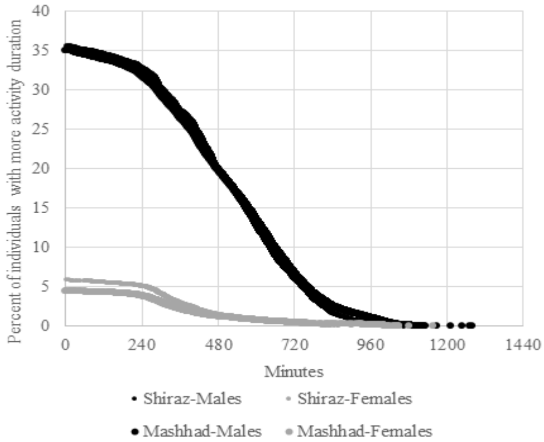
This section presents the results of applying the introduced model transfer methods on the estimated models. Different sample sizes (1, 5, 10, 20, 30, 40, and 50 percent of the entire data) are drawn with replacement to determine the effect of the application context's sample size on the transferred models' prediction accuracy. For each size category, five subsamples are drawn, leading to 35 different subsamples. For each subsample, all the transfer methods are performed along with calculating the transferability assessment metrics.

Table 4. Descriptive statistics of demographics, activity type and duration

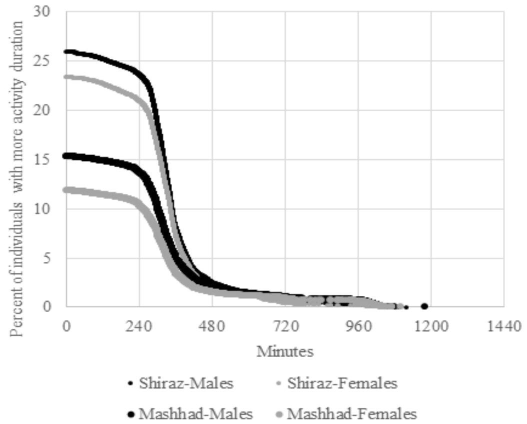
City	Mashhad		Shiraz	
Sample size	61,036		42,969	
Number of TAZs	141		156	
Socio-demographic characteristics				
Male	52.0%		51.1%	
Age: 6 - 12 years	26.9%		17.5%	
Age: 13 - 18 years	21.3%		23.7%	
Age: 19 - 24 years	9.4%		13.1%	
Age: 25 - 35 years	17.2%		17.2%	
Age: 36 - 45 years	13.8%		16.1%	
Age: 46 - 60 years	8.7%		9.6%	
Age: > 60 years	2.7%		2.8%	
Clerk, Teacher, Army	9.2%		11.0%	
Labour, Farmer, Workman	8.9%		6.6%	
Driver	1.7%		1.9%	
Seller	4.5%		5.5%	
Student	45.6%		44.2%	
Unemployed	27.8%		28.6%	
Average household size	4.98		4.00	
Bikes per capita	0.09		0.07	
Motorcycles per capita	0.06		0.04	
Cars per capita	0.06		0.10	
Pickups per capita	0.01		0.01	
Aggregate activity participation (% who participated) and average activity duration (among those who participated)				
Activity types	**Participated (%)**	**Duration (min)**	**Participated (%)**	**Duration (min)**
In-home activities	100	1208	100	1179
Work	20.3	515	21.3	502
Education	13.7	371	24.7	350
Shopping	7.3	123	9.4	129
Personal business	1.2	154	2.0	154
Healthcare	1.9	148	2.8	164
Visiting relatives	8.9	199	7.0	200
Recreation	5.5	142	3.3	152
Travel	46.3	68	60.9	36
Other	6.1	106	3.5	178



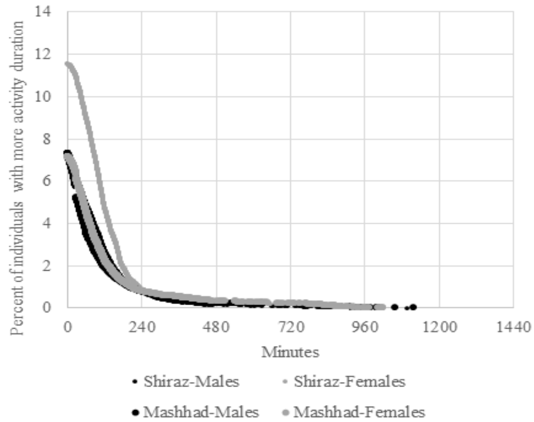
(a) In-home



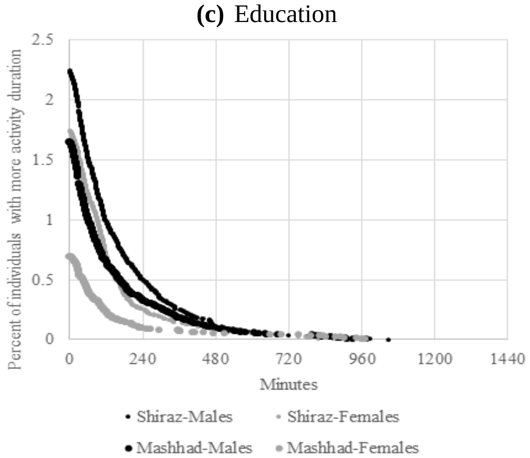
(b) Work



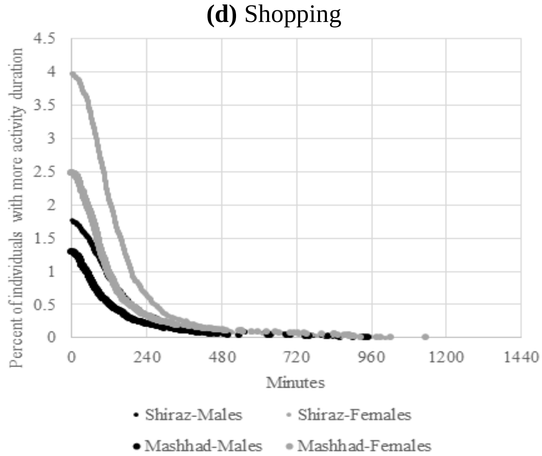
(c) Education



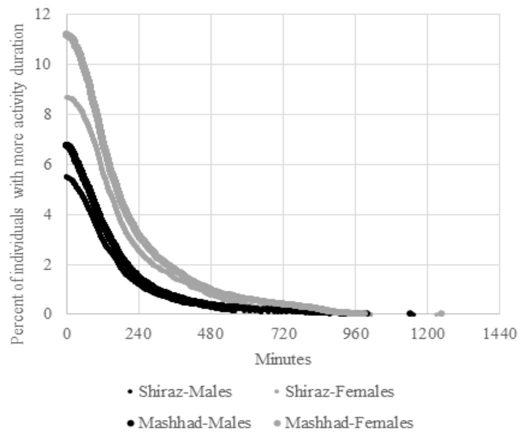
(d) Shopping



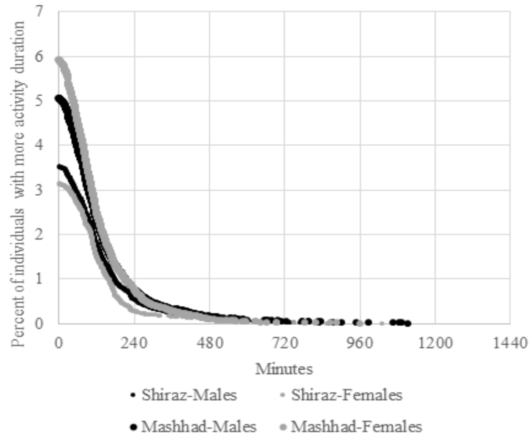
(e) Personal business



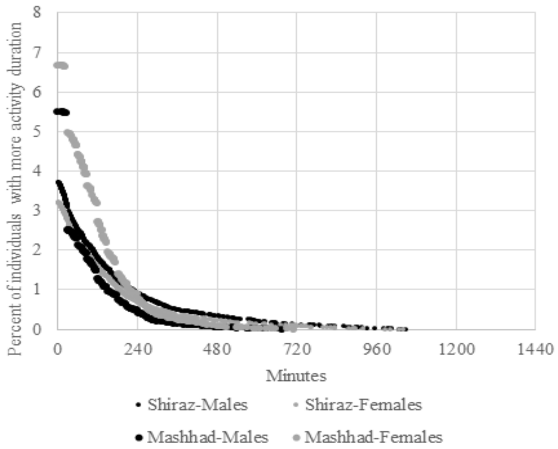
(f) Healthcare



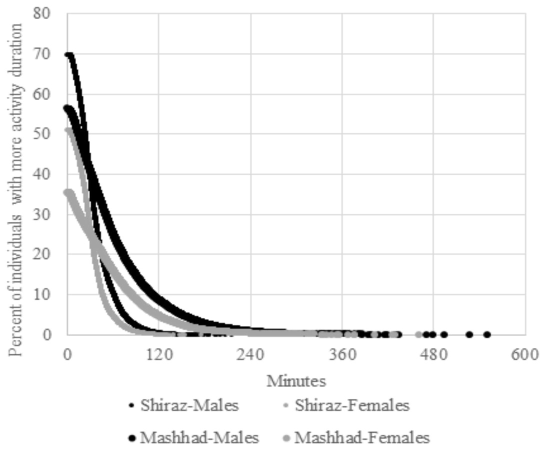
(g) Visiting Family/Friends



(h) Entertainment/Religious



(i) Other Activities



(j) Daily Travel

Fig. 1. Activity time allocations of individuals in Shiraz and Mashhad

Table 5. Summary of model estimation results

Context	Shiraz	Mashhad
Number of observations used in model estimation	34,469	49,036
Log-likelihood value (in convergence)	-8,422,053	-10,878,470
Log-likelihood value (constants-only model)	-9,006,066	-11,621,623
ρ^2	%6.48	%6.40
Run time (hours)	27.20	43.85

The detailed results of the transferability assessment metrics are presented in the appendix (Table A4). However, the distribution of selected transferability assessment metrics for each sample size and transfer method is presented in Figures 2 to 5. As expected, the larger the application context's sample size, the better the transferred model's prediction performance. Likewise, switching from simple transfer methods to more advanced techniques result in better prediction performance of the transferred model.

The Transferability Test Statistic (TTS) assessment metric results are presented in Table A4 of the appendix. The critical value for χ^2 distribution with degrees of freedom equal to the number of model parameters is 242.767. The numbers illustrate that transferred model parameters are statistically equal to the application context model parameters in higher sample sizes for the Bayesian updating, *combined transfer estimation*, and joint context estimation methods.

The locally estimated model in Mashhad using the entire data has ρ^2-Transferred equal to 6.00 percent. None of the transfer scaling methods obtain this value in any sample size. While Bayesian updating reaches this value in a 50 percent sample size, the combined transfer estimation method achieves this value in a 40 percent sample size. The critical point is that the joint context estimation method reaches a higher value than 6.00 percent in 20 percent of the application context sample size. Thus, the joint context estimation method outperforms other methods in fitting application context data relative to a reference model.

Transfer Index (TI) measures the goodness-of-fit of a transferred model with respect to a similar model specification in the application context. Based on the TI values, only joint context estimation in 20 percent and combined transfer estimation in 30 percent of the sample size reach that of the Mashhad model.

Root-Mean-Square Error (RMSE) and Relative Aggregate Transfer Error (RATE) show that estimating the application context model and Bayesian updating methods exceed the Mashhad model's values in a 40 percent sample size. Therefore, using data from two regions with somehow similar characteristics improves the model's predictive power. The joint context estimation reaches the local model's value in RMSE and RATE measures, with a 30 percent sample size. These measures show that the joint context estimation method outperforms other methods in aggregate-level prediction performance of the transferred model, expectedly. The detailed average values of transferability assessment metrics calculated over the 20 percent reserved data for each transfer method are accessible in the appendix.

4.3. Transferred Models Forecasting Power

Since travel behavior models are mainly used for forecasting and policy analysis, comparing the model results under different scenarios is highly recommended (Sikder and Pinjari, 2013). In this study, a hypothetical scenario is assumed to increase each individual's age by ten years and a 50 percent increase in car ownership. Table 6 illustrates the prediction of aggregate time allocation to each activity type for the locally estimated model using the complete sample and the transferred models with a 10 percent sample size. The results show that the closest predictions to the local model result from a joint context estimation method indicating this method's superiority to other methods. Combined transfer estimation, Bayesian updating, and estimating the application context model methods also provided close aggregate predictions to the local model.

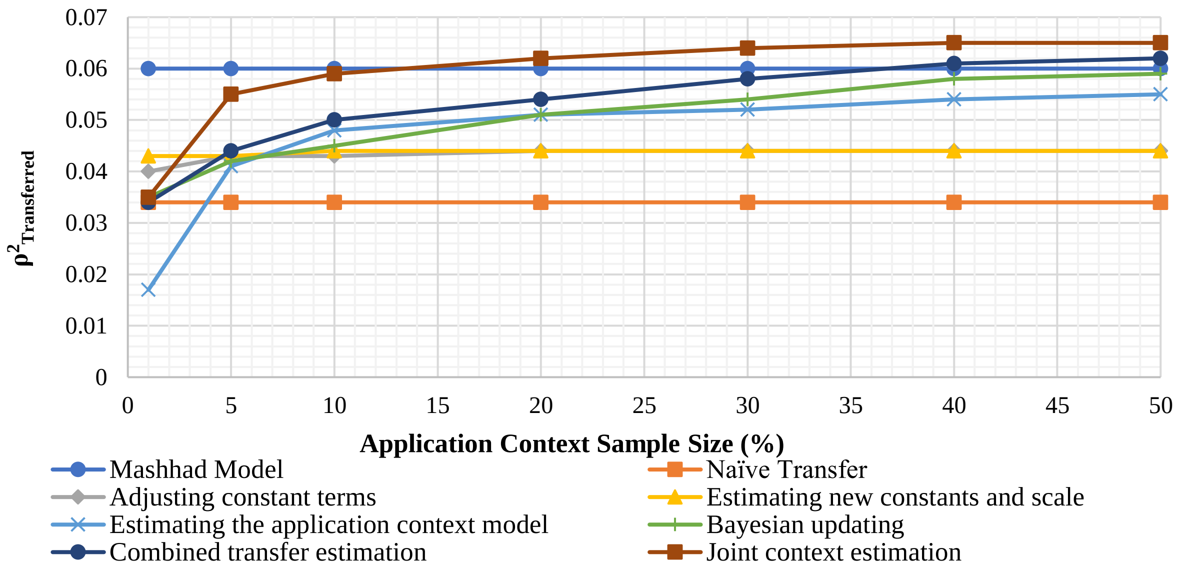


Fig. 2. $\rho^2_{Transferred}$ of each transfer method against application context sample sizes

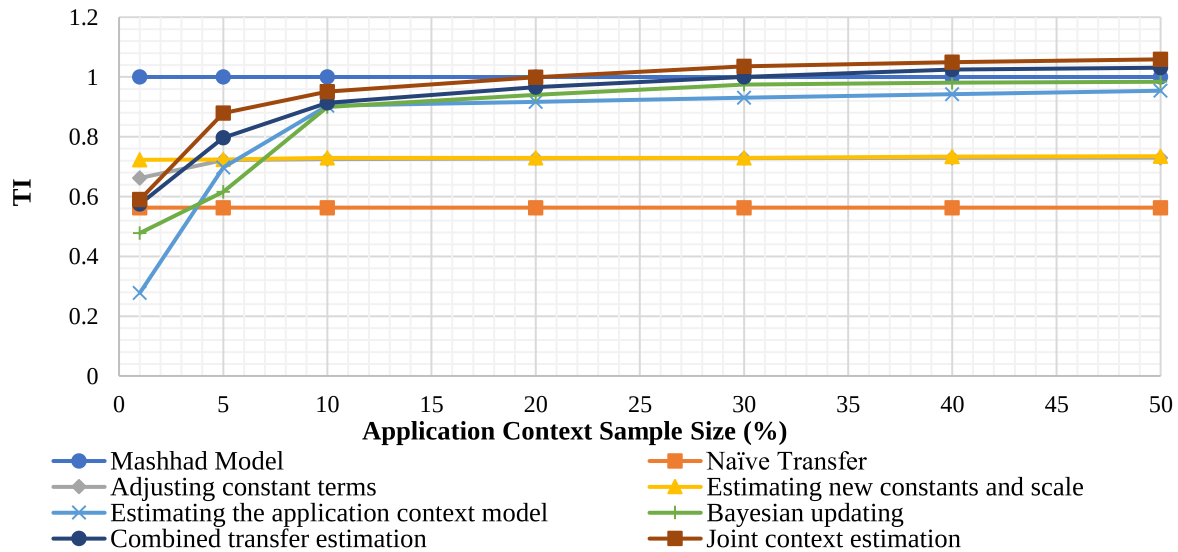


Fig. 3. Transfer Index of each transfer method against application context sample sizes

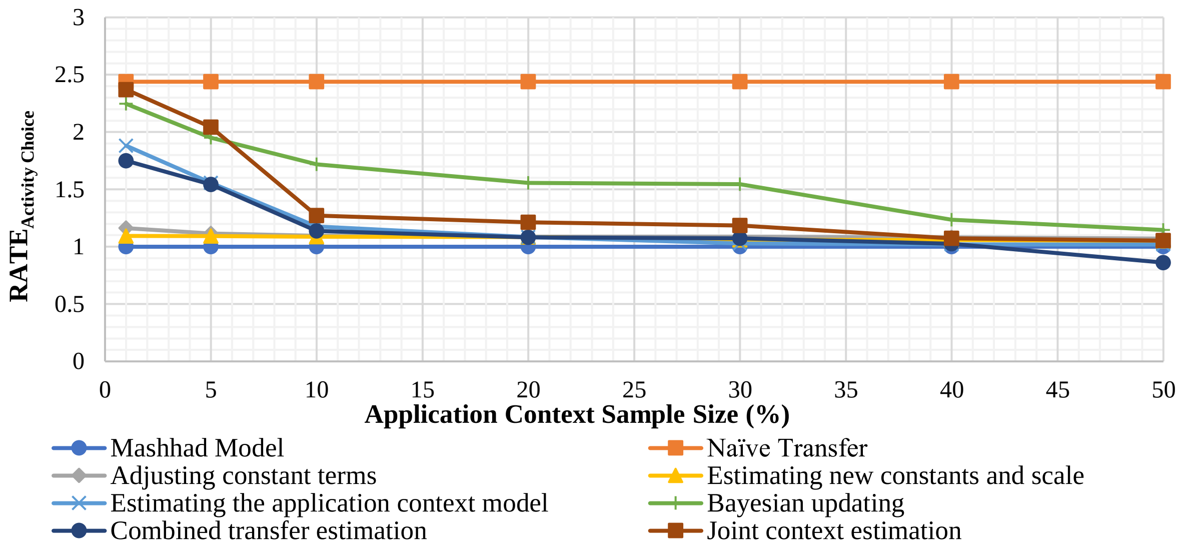


Fig. 4. RATE index of activity choices of each transfer method against application context sample sizes

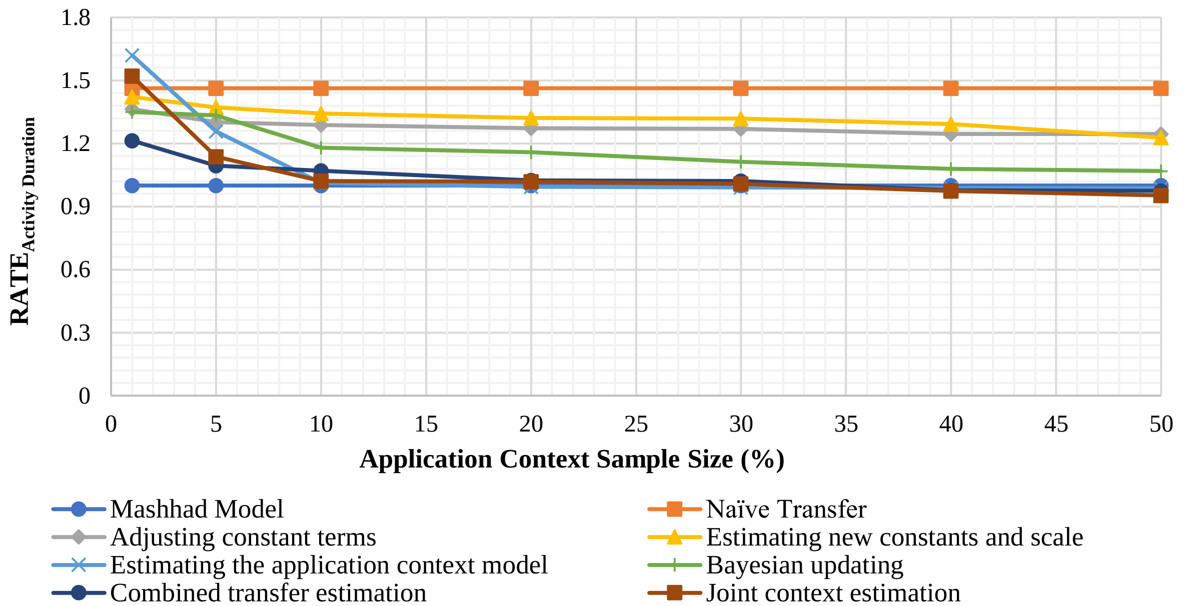


Fig. 5. RATE index of activity durations of each transfer method against application context sample sizes

Table 6. Activity time (min) allocation in local versus transferred models for a hypothetical scenario*

Model	In-home	Work	Education	Shopping	Personal business	Health care	Visiting relatives	Recreation	Travel	Other
Mashhad model (100% sample size)	1074	111	44	23	9	12	23	18	16	54
Naive transfer	1220	80	37	9	7	8	10	10	13	44
Adjusting constants	1197	83	44	10	7	10	10	10	14	40
Estimating new constants and scale	1123	89	50	12	7	10	26	17	15	33
Estimating the Application context model	1135	160	27	10	8	9	14	17	12	41
Bayesian updating	1113	129	30	14	7	9	18	15	13	40
Combined transfer estimation	1109	132	39	14	7	8	21	17	13	42
Joint context estimation	1102	107	47	18	8	11	21	17	15	45

* 10 years increase in age and 50 percent increase in car ownership

Table 7 provides sample size effects on the joint context estimation method's predictions in the same previous scenario. The larger the estimation context sample, the closer are the predictions to the locally estimated model. The average absolute difference between the local and the transferred model outputs was 3.6 percent for the 50 percent sample, 4.3 percent for the 40 percent sample, 5.5 percent for the 30 percent sample, 6.8 percent for the 20 percent sample, 8.9 percent for the 10 percent sample, 15.0 percent for the 5 percent sample, and 29.8 percent for the 1 percent sample. According to the results, the prediction accuracy improvement rate starts diminishing when the sample size passes the 10 percent value. For the 10 percent sample, however, the average absolute difference between the local and the transferred model outputs was 2.6 percent for in-home, 3.7 percent for work, 5.0 percent for education, 5.6 percent for travel, 5.8 percent for recreation, 6.3 percent for visiting relatives, 8.8 percent for personal business, 17.7 percent for other, and 22.5 percent for shopping. Mandatory activities, understandably, are more convenient to transfer than irregular activities. Another observation is that as the sample size increases, predicted activity durations also increase, except for in-home activity. In other words, all the activity durations are underestimated in small samples, except for in-home activity.

5. Summary and Conclusions

This paper presented an empirical assessment of the spatial transferability of MDCEV models for activity type and duration in two major cities of Iran, Shiraz and Mashhad. The transfer methods used were transfer scaling, Bayesian updating, combined transfer estimation, and joint context estimation. Then, transferability assessment metrics were presented for each approach. Transferability was evaluated using log-likelihood-based measures and aggregate and disaggregate predictability of the transferred model. The policy predictability of the models was also evaluated and discussed for a hypothetical policy.

The results shed light on the prediction properties of the transferred MDCEV model using different transfer methods and different sample sizes of the application context data. The findings of this study are as follows:

First, joint context estimation and combined transfer estimation are the most appropriate transfer methods if limited data from the application context is available. Nonetheless, the combined transfer estimation provided closer outputs for the presented scenario compared to the local model. Second, although the increase in application context data improves the transfer model's predictability, a sample size of 10 percent of the application context data provides encouraging results. Third, combined transfer estimation had encouraging policy predictability when a hypothetical scenario was tested on age and car ownership increase. Therefore, the transferred model can have a comparable prediction to the locally estimated model for policy analysis and forecast. Besides, an appropriate model transfer can significantly reduce the costs of conducting household travel surveys, shorten the time interval between transportation studies in a given city, and result in more accurate travel behavior models. However, determining the proper application sample size depends on the data collection costs and the desired performance level. This research and other similar studies could lead to the accumulation of empirical evidence in transferring travel demand models and provide a picture of sample size and accuracy trade-offs.

The current study can be extended in several ways:

Table 7. Activity time (min) allocation for different sample sizes in a hypothetical scenario*

Model	Sample size (%)	In-home	Work	Education	Shopping	Personal business	Health care	Visiting relatives	Recreation	Travel	Other
Mashhad model	100	1074	111	44	23	9	12	23	18	16	54
Joint context estimation	1	1187	79	38	11	6	8	14	11	11	43
	5	1119	86	43	17	7	9	21	15	14	44
	10	1102	107	47	18	8	11	21	17	15	45
	20	1087	107	47	18	8	11	22	18	15	48
	30	1078	110	47	18	8	11	22	18	15	48
	40	1075	111	47	19	8	12	22	18	16	48
	50	1072	111	47	19	8	12	23	18	16	49

* 10 years increase in age and 50 percent increase in car ownership

- The cities considered in this study have almost the same demographics. An interesting approach could be transferring an estimated model from a large city to a small city since small cities have a more limited budget to conduct comprehensive travel surveys and can greatly benefit from transferring models to their jurisdictions.
- Other model specifications in the MDCEV family should be specifically investigated since more evidence is required for generalization of this study’s findings to other modeling specifications, data sources, or contexts.
- The scale of the random utility components was presumed to be similar across both contexts.
- Scale differences across both regions can potentially shed more light on model transferability.
- Although segmentation of the data by individual characteristics can benefit, this study did not consider such a procedure since the aim here is to analyze the transferability of the MDCEV model as a whole package considering different transfer methods and sample sizes. A future study can investigate the impacts of data segmentation and exploration of each segment's activity type and time allocation similarities and dissimilarities.

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Appendix

Table A1. MDCEV model results for Shiraz

Variable	**Activity type**									
	In-home	**Work**	**Education**	**Shopping**	**Personal business**	**Health care**	**Visiting relatives**	**Recreation**	**Travel**	**Other**
Constant	**4.938**	**-1.894**	**-6.446**	**-3.815**	**-3.981**	**-5.841**	**-3.753**	**-3.977**		**-4.440**
	323.26	**-73.43**	**-30.09**	**-126.65**	**-79.91**	**-109.51**	**-123.07**	**-91.37**		**-101.62**
Individual Characteristics										
Age 6 - 12 years	1.653	-4.048	6.246	-0.189	-2.500	-0.504	0.243	0.840	0.563	
	32.43	-40.66	28.46	-3.15	-21.18	-6.40	4.32	12.84	10.91	
Age 13 - 18 years	0.226	-1.758	5.545	-0.514	-1.674	-1.013	-0.469	0.390	0.110	
	5.68	-39.23	25.53	-11.16	-27.19	-16.92	-10.62	7.43	2.72	
Age 19 - 24 years	-0.565	-0.643	3.895	-0.695	-1.007	-1.002	-0.700	-0.379	-0.621	
	-15.68	-16.37	17.98	-17.34	-19.78	-21.01	-17.30	-8.08	-16.93	
Age 25 - 35 years	-0.548	-0.292	2.853	-0.226	-0.806	-0.717	-0.575	-0.305	-0.438	
	-16.00	-7.87	13.17	-5.98	-16.93	-16.11	-15.04	-6.82	-12.58	
Age 36 - 45 years	-0.570	-0.257	1.737	-0.043	-0.831	-0.660	-0.623	-0.508	-0.331	
	-16.7	-6.81	7.93	-1.13	-17.08	-14.63	-15.99	-10.99	-9.35	
Age 46 - 60 years	-0.700	-0.423	0.704	-0.275	-0.846	-0.622	-0.693	-0.666	-0.410	
	-20.18	-11.22	3.11	-7.23	-17.59	-13.93	-17.89	-14.52	-11.60	
Female	0.545	-0.232	0.517	0.331	-0.154	0.877	0.437	-0.219	0.257	
	35.00	-13.39	31.85	18.39	-6.08	36.65	23.49	-10.28	16.32	
White-collar worker	-0.134	1.419	-2.487	0.113	0.066	0.021		-0.292	0.039	
	-7.57	66.78	-75.28	4.32	1.99	0.49		-8.31	2.17	
Blue-collar worker	0.322	2.087	-3.556	0.336		0.376	0.241	-0.088	0.560	
	12.45	73.64	-59.38	9.82		6.95	7.43	-1.98	21.39	
Driver	-0.209	0.883	-2.948	-0.708	-0.570	0.414	0.074	-0.847	-0.339	
	-5.51	21.95	-32.24	-13.31	-8.49	6.17	1.62	-11.61	-8.80	
Seller	0.198	1.666	-4.257	0.155	-0.235	0.142	-0.027	-0.324	0.258	
	6.91	53.72	-42.77	4.26	-5.01	2.51	-0.80	-6.79	8.88	
Student	-0.353	-1.722	-0.091	0.037	0.268	0.165	-0.368	0.222	-0.350	
	-12.30	-47.19	-3.02	1.00	5.95	3.14	-10.51	5.35	-12.02	
Unemployed	-0.126	-2.242	-3.144	0.759	-0.054	0.595	0.570	0.493	-1.163	
	-5.85	-83.21	-112.86	27.29	-1.54	14.36	26.31	15.09	-52.90	
Household characteristics										
Household size	0.116	0.046	0.004	-0.007	0.052	0.052	-0.040	0.022	-0.009	
	34.65	12.89	1.09	-1.77	9.82	10.75	-9.84	4.57	-2.66	
Living in CBD	-0.073	-0.140	-0.291	-0.365	-0.141	-0.411	0.039	-0.006	-0.335	
	-3.60	-6.53	-13.34	-14.86	-3.99	-12.98	1.68	-0.22	-16.60	
Bike capita	-0.300	-0.147	0.212	0.424		-0.060	0.259	-0.123	0.229	
	-7.78	-3.45	4.93	9.29		-0.93	5.38	-2.03	5.85	
Motorcycle capita	0.559	0.878	0.454	0.632	0.232	0.086	0.790	0.295	0.490	
	8.66	13.00	6.45	8.79	2.27	0.91	10.69	3.32	7.51	
Car capita	-1.051	-0.525	-0.138	-0.955	-1.113	-0.894	-0.358	-0.585	-0.680	
	-27.94	-12.96	-3.26	-21.92	-17.08	-15.63	-8.01	-10.61	-17.87	
Pickup capita	-0.076	-0.075			-0.429		0.702		-0.159	-0.476
	-1.65	-1.11			-2.50		8.83		-3.18	-3.62
Presence of child below 12 years	-0.089	-0.090		-0.076	0.003	-0.125	-0.016	-0.161	-0.052	
	-14.85	-11.23		-7.85	0.20	-8.04	-1.49	-10.99	-8.26	
Residing TAZ characteristics										
Recreation land use share	0.008							-0.321		
	0.64							-5.53		
Commercial land use share	-0.366			3.824						
	-2.82			12.99						
Land use Diversity Index	0.018	0.023	0.033	0.018	0.031	0.469	-0.294	-0.269	-0.113	
	0.43	0.52	0.75	0.37	0.46	7.54	-5.90	-4.53	-2.67	
Translation parameter										
γ	0	266.742	193.187	87.839	111.725	137.603	167.914	131.103	118.559	9.117
	-	1106.63	120.93	791.74	359.07	461.62	749.86	491.72	463.52	830.78
Number of observations							34,469			
Log-likelihood value (in convergence)							-8,422,053.2			
Log-likelihood value (constants-only model)							-9,006,066.1			
ρ^2							6.48%			
Run time (hours)							27.20			

Table A2. MDCEV model results for Mashhad

Variable	Activity type									
	In-home	**Work**	**Education**	**Shopping**	**Personal business**	**Health care**	**Visiting relatives**	**Recreation**	**Travel**	**Other**
Constant	**4.839**	**-1.999**	**-4.275**	**-3.163**	**-4.015**	**-5.644**	**-3.714**	**-3.298**		**-3.325**
	358.93	**-91.72**	**-51.27**	**-121.16**	**-72.06**	**-109.08**	**-152.57**	**-120.61**		**-131.98**
Individual characteristics										
Age 6 - 12 years	2.739	-1.299	4.180	0.649	-1.553	0.928	1.456	0.546	0.540	
	108.78	-31.57	48.83	18.98	-13.49	16.95	47.31	16.01	20.53	
Age 13 - 18 years	1.598	0.590	4.364	0.802	-0.748	0.701	0.967	0.736	0.985	
	73.73	22.24	51.55	27.44	-10.93	14.63	35.10	25.3	43.49	
Age 19 - 24 years	0.738	0.889	3.284	0.569	0.892	0.546	0.762	0.313	0.621	
	38.71	37.69	38.93	22.1	18.09	13.52	30.62	12.24	30.94	
Age 25 - 35 years	0.423	1.054	2.149	0.672	0.845	0.731	0.758	0.075	0.662	
	24.90	49.36	25.53	29.11	18.42	19.97	33.62	3.24	36.99	
Age 36 - 45 years	0.130	0.826	1.094	0.561	0.581	0.364	0.625	-0.111	0.550	
	7.51	38.05	12.67	23.82	12.36	9.65	27.12	-4.63	30.10	
Age 46 - 60 years	-0.016	0.595	0.249	0.253	0.487	0.015	0.348	-0.087	0.392	
	-0.96	27.53	2.70	10.87	10.63	0.40	15.25	-3.75	21.73	
Female	0.448	-0.643	0.218	-0.236	-0.996	0.377	0.376	-0.216	-0.124	
	41.93	-49.47	18.44	-16.75	-34.27	16.92	28.34	-14.89	-11.28	
White-collar worker	0.0356	1.514	-1.516	-0.06	0.173	0.334		-0.78	0.307	
	2.91	102.39	-68.17	-0.33	6.22	8.94		-12.42	24.01	
Blue-collar worker	0.120	1.869	-3.488	-0.003		0.681	0.018	-0.166	0.534	
	7.81	107.56	-84.75	-0.15		18.15	0.92	-7.03	33.71	
Driver	-0.050	0.856	-3.684	-0.594	-0.325	0.132	0.060	-0.722	-0.240	
	-1.87	29.87	-31.32	-15.07	-5.94	2.03	1.79	-15.70	-8.75	
Seller	0.227	1.649	-3.591	0.482	0.337	0.148	-0.001	-0.254	0.282	
	11.35	78.83	-51.52	18.98	9.72	2.95	-0.04	-8.4	13.81	
Student	-0.326	-1.054	0.234	-0.490	-0.276	-0.511	-0.435	-0.259	-0.031	
	-12.85	-33.22	8.58	-13.66	-5.18	-7.70	-13.42	-7.10	-1.19	
Unemployed	-0.569	-2.679	-3.798	-0.057	-0.414	0.261	-0.126	0.145	-1.285	
	-40.83	-131.67	-158.32	-2.94	-12.74	7.74	-8.28	7.27	-87.90	
Household characteristics										
Household size	0.075	0.013	-0.065	-0.025	0.003	-0.001	-0.083	0.005	-0.063	
	39.63	5.95	-27.89	-10.02	0.73	-0.15	-33.46	1.72	-31.64	
Living in CBD	-0.012	0.067	0.094	0.092	-0.368	0.128	0.359	-0.141	-0.103	-0.012
	-0.80	3.87	5.02	4.41	-8.58	4.31	19.58	-6.36	-6.49	-0.80
Bike capita	-0.636	-0.197	0.177	0.253		0.026	-0.244	0.265	0.093	
	-23.37	-6.31	5.22	7.09		0.45	-7.05	6.97	3.34	
Motorcycle capita	-0.533	-0.296	-0.808	0.008	-0.494	0.039	0.276	0.261	-0.782	
	-16.60	-8.19	-18.91	0.21	-6.23	0.63	7.20	6.06	-23.54	
Car capita	0.000	0.539	1.515	0.725	1.482	0.485	0.931	0.142	0.022	
	0.01	14.65	37.78	17.58	22.23	7.66	24.06	3.11	0.66	
Pickup Capita	-0.078	0.509			0.259		0.674		-0.024	-0.556
	-1.69	7.88			1.41		9.19		-0.27	-10.74
Presence of child below 12 years	-0.061	-0.024		0.026	0.107	0.027	0.058	-0.078	-0.005	
	-10.24	-3.09		2.62	5.04	1.55	6.21	-7.18	-0.85	
Residing TAZ characteristics										
Recreation land use share	-0.154							-0.063		
	-8.21							-1.24		
Commercial land use share	0.290			3.905						
	29.08			1.60						
Land use diversity index	-0.366	-0.526	-0.885	-0.479	-0.763	-1.284	-0.392	0.066	-0.488	
	-12.26	-16.18	-25.53	-12.70	-11.03	-22.21	-10.87	1.47	-16.40	
Translation parameter										
γ	0	314.891	345.102	71.891	92.938	109.292	152.922	109.988	73.525	19.722
	-	1318.63	1240.00	768.76	315.96	427.26	981.75	752.00	730.91	1219.95
Number of observations							49,036			
Log-likelihood value (in convergence)							-10,878,470.7			
Log-likelihood value (constants-only model)							-11,621,923.3			
ρ^2							6.40%			
Run time (hours)							43.85			

Table A3. t-test of difference between coefficient estimates*

Variable	Activity type: In-home	Work	Education	Shopping	Personal business	Health care	Visiting relatives	Recreation	Travel	Other
Constant	**4.86**	**3.11**	**-9.44**	**-16.36**	**0.45**	**-2.65**	**-1.00**	**-13.21**		**-22.11**
Individual characteristics										
Age 6 - 12 years	-19.10	-25.52	8.77	-12.13	-5.74	-14.93	-18.92	3.99	0.40	
Age 13 - 18 years	-30.28	-45.09	5.07	-24.13	-10.06	-22.35	-27.59	-5.77	-18.88	
Age 19 - 24 years	-31.96	-33.44	2.63	-26.53	-26.79	-24.77	-30.78	-12.95	-29.70	
Age 25 - 35 years	-25.40	-31.44	3.03	-20.28	-24.97	-25.13	-30.03	-7.55	-28.10	
Age 36 - 45 years	-18.29	-24.88	2.73	-13.50	-20.87	-17.41	-27.57	-7.62	-22.11	
Age 46 - 60 years	-17.77	-23.43	1.86	-11.84	-20.07	-10.92	-23.15	-11.26	-20.21	
Female	5.14	18.98	14.89	24.81	21.84	15.29	2.67	-0.12	19.84	
White-collar worker	-7.88	-3.67	-24.38	0.94	-2.47	-5.51		6.78	-12.15	
Blue-collar worker	6.71	6.56	-0.94	8.55		-4.63	5.89	1.55	0.85	
Driver	-3.43	0.55	4.94	-1.72	-2.83	3.02	0.25	-1.45	-2.09	
Seller	-0.83	0.45	-5.48	-7.37	-9.81	-0.08	-0.62	-1.24	-0.68	
Student	-0.70	-13.81	-8.00	10.23	7.80	7.99	1.40	8.71	-8.16	
Unemployed	17.27	12.94	17.79	24.07	7.53	6.25	26.29	9.09	4.62	
Household characteristics										
Household size	10.66	7.89	15.87	3.85	7.31	6.43	9.03	3.02	13.75	
Living in CBD	-2.42	-7.51	-13.39	-14.18	4.08	-12.42	-10.82	3.84	-9.04	
Bike capita	7.12	0.95	0.64	2.95		-0.99	8.48	-5.42	2.83	
Motorcycle capita	15.15	15.33	15.33	7.67	5.61	0.42	6.17	0.34	17.37	
Car capita	-27.94	-19.44	-28.35	-28.00	-27.84	-16.16	-21.80	-10.16	-13.88	
Pickup capita	0.03	-6.25			-2.74		0.26		-1.32	0.57
Presence of child below 12 years	-3.31	-5.91		-7.36	-4.00	-6.51	-5.20	-4.55	-5.46	
Residing TAZ characteristics										
Recreation land use share	7.19							-3.34		
Commercial land use share	-5.04									
Land use Diversity Index	7.47	10.00	16.39	8.07	8.22	20.64	1.59	-4.50	7.25	
Translation parameter										
γ		-141.91	-93.68	109.91	43.88	72.08	54.96	69.43	163.85	-542.76

*Statistically different if the value is bigger than 2 with %95 confidence interval

Table A4. Transferability assessment metrics

Transfer method	Percent of application context data	LL_1 (*10[6])	$LL_{Transferred}$ (*10[6])	$LL_{Constants\ Only}$ (*10[6])	TTS (*10[3])	$\rho^2_{Transferred}$	TI	$RMSE_{Activity\ Type}$	$RMSE_{Activity\ Duration}$	$RATE_{Activity\ Type}$	$RATE_{Activity\ Duration}$	$APS_{Activity\ Type}$	$APS_{Activity\ Duration}$
Mashhad model	100	-2.661	-2.735	-2.830	0	0.060	1.000	0.135	0.296	1.000	1.000	0.085	21.467
Naïve transfer	0	-2.661	-2.661	-2.830	148	0.034	0.563	0.329	0.433	2.439	1.463	0.251	42.291
Adjusting constant terms	1	-2.661	-2.718	-2.830	115	0.040	0.662	0.151	0.404	1.162	1.364	0.088	38.429
	5	-2.661	-2.708	-2.830	94.3	0.043	0.722	0.157	0.385	1.116	1.301	0.085	36.808
	10	-2.661	-2.707	-2.830	93.0	0.043	0.725	0.147	0.381	1.096	1.288	0.074	37.249
	20	-2.661	-2.708	-2.830	92.4	0.044	0.727	0.148	0.377	1.088	1.273	0.073	36.743
	30	-2.661	-2.707	-2.830	92.1	0.044	0.728	0.146	0.376	1.088	1.270	0.072	38.443
	40	-2.661	-2.707	-2.830	92.0	0.044	0.729	0.145	0.369	1.081	1.246	0.071	36.970
	50	-2.661	-2.707	-2.830	91.5	0.044	0.730	0.147	0.369	1.071	1.245	0.070	35.886
Estimating new constants and scale	1	-2.661	-2.705	-2.830	93.7	0.043	0.723	0.143	0.421	1.094	1.422	0.082	36.857
	5	-2.661	-2.708	-2.830	93.1	0.043	0.724	0.143	0.406	1.093	1.372	0.081	36.765
	10	-2.661	-2.707	-2.830	91.7	0.044	0.729	0.143	0.398	1.088	1.343	0.080	36.957
	20	-2.661	-2.707	-2.830	91.7	0.044	0.730	0.148	0.394	1.085	1.321	0.076	36.487
	30	-2.661	-2.707	-2.830	91.4	0.044	0.730	0.148	0.391	1.060	1.318	0.076	34.955
	40	-2.661	-2.706	-2.830	90.0	0.044	0.734	0.142	0.390	1.058	1.293	0.075	35.743
	50	-2.661	-2.706	-2.830	90.0	0.044	0.735	0.147	0.383	1.050	1.228	0.071	37.204

Estimating the application context model	1	-2.661	-2.783	-2.830	245	0.017	0.278	0.294	0.380	1.881	1.620	0.370	96.876
	5	-2.661	-2.678	-2.830	34.8	0.041	0.697	0.254	0.372	1.557	1.258	0.314	95.688
	10	-2.661	-2.660	-2.830	-1.19	0.048	0.904	0.210	0.300	1.176	1.013	0.254	67.432
	20	-2.661	-2.658	-2.830	-5.77	0.051	0.917	0.146	0.294	1.085	0.994	0.092	29.402
	30	-2.661	-2.656	-2.830	-10.6	0.052	0.931	0.139	0.288	1.028	0.991	0.089	26.718
	40	-2.661	-2.654	-2.830	-14.5	0.054	0.943	0.138	0.275	1.021	0.988	0.084	26.260
	50	-2.661	-2.652	-2.830	-18.3	0.055	0.954	0.129	0.246	1.019	0.987	0.082	25.576
Bayesian updating	1	-2.661	-2.733	-2.830	245	0.035	0.478	0.303	0.400	2.246	1.350	0.277	85.955
	5	-2.661	-2.726	-2.830	130	0.042	0.616	0.263	0.395	1.951	1.333	0.245	72.938
	10	-2.661	-2.661	-2.830	29.2	0.045	0.900	0.232	0.350	1.720	1.180	0.239	55.895
	20	-2.661	-2.657	-2.830	20.3	0.051	0.940	0.210	0.343	1.557	1.159	0.194	39.797
	30	-2.661	-2.656	-2.830	0.61	0.054	0.975	0.210	0.330	1.545	1.113	0.172	35.164
	40	-2.661	-2.676	-2.830	-8.40	0.058	0.981	0.167	0.316	1.234	1.080	0.141	27.592
	50	-2.661	-2.671	-2.830	-10.6	0.059	0.984	0.155	0.304	1.146	1.069	0.134	26.225
Combined transfer estimation	1	-2.661	-2.783	-2.830	144	0.034	0.575	0.236	0.360	1.750	1.214	0.234	76.585
	5	-2.661	-2.678	-2.830	34.9	0.044	0.797	0.208	0.324	1.543	1.094	0.145	65.777
	10	-2.661	-2.661	-2.830	0.61	0.05	0.914	0.169	0.304	1.138	1.070	0.123	59.078
	20	-2.661	-2.657	-2.830	-5.44	0.054	0.966	0.146	0.302	1.083	1.025	0.093	30.102
	30	-2.661	-2.656	-2.830	-8.40	0.058	1.000	0.145	0.295	1.072	1.021	0.090	28.219
	40	-2.661	-2.658	-2.830	-10.6	0.061	1.025	0.138	0.290	1.025	0.978	0.084	26.606
	50	-2.661	-2.652	-2.830	-18.3	0.062	1.031	0.116	0.289	0.862	0.975	0.054	26.434
Joint context estimation	1	-2.661	-2.730	-2.830	139	0.035	0.590	0.320	0.426	2.371	1.521	0.287	69.448
	5	-2.661	-2.724	-2.830	114	0.055	0.879	0.226	0.361	2.042	1.138	0.234	57.208
	10	-2.661	-2.720	-2.830	11.8	0.059	0.951	0.187	0.293	1.272	1.022	0.112	39.833
	20	-2.661	-2.720	-2.830	1.02	0.062	0.999	0.145	0.278	1.213	1.018	0.103	30.647
	30	-2.661	-2.719	-2.830	0.90	0.064	1.036	0.135	0.261	1.186	1.008	0.095	26.062
	40	-2.661	-2.719	-2.830	-8.85	0.065	1.050	0.123	0.261	1.074	0.974	0.084	24.039
	50	-2.661	-2.718	-2.830	-9.82	0.065	1.059	0.112	0.242	1.053	0.953	0.052	23.637