Spatial Transferability of Person-Level Daily Activity Generation and Time-Use Models: An Empirical Assessment

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ABSTRACT

This paper presents an empirical assessment of the spatial transferability of person-level daily activity generation and time-use models among different regions in Florida and between Florida and California. The empirical models are for unemployed adults based on the multiple discrete-continuous extreme (MDCEV) structure. An examination of the prediction properties of the MDCEV model is provided first. The results shed new light on the prediction properties of the MDCEV model that have implications to transferability, as well as provide insights into how the model structure can potentially be improved. Transferability was evaluated for two approaches to transferring models – naïve transfer and updating model constants – using different measures such as log-likelihood based metrics, aggregate predictive ability, and model sensitivity to changes in demographic characteristics. Results suggest that accurate prediction of aggregate observed patterns is not an adequate yardstick to assess transferability; emphasis should be placed on model sensitivity to changes in explanatory variables. Updating constants helps in improving a transferred model's aggregate prediction ability but not necessarily in improving its policy sensitivity. The extent of transferability between different regions within a state is greater than that across different states. Within Florida, there is greater transferability between urban regions (especially between Southeast Florida and Central Florida regions) than between urban and rural regions.

1 BACKGROUND

Spatial transferability of travel forecasting models can help in significant cost savings for regions that cannot afford to invest in extensive data collection and model development procedures. This issue is particularly important for tour-based/activity-based models (ABMs) whose development typically involves significant data inputs and long production times.

The literature abounds with empirical studies on this topic (see *1, 2, & 3* for recent reviews). However, most work to date has been devoted to the transferability of linear regression-based travel generation models and logit-based mode-choice models. Few studies focus on travel choices other than trip generation or mode-choice and on econometric model structures other than linear regression, ordered response, or multinomial logit. Transferability assessments in the context of tour-based/activity-based model systems are much fewer. Only a handful of studies (e.g., *4, 5, & 6*) document the transferability assessment of activity-based model systems to varying degrees, while some recent efforts are underway (e.g., the SHRP-2 C10 studies) and a few studies focus on the transferability of specific components of ABMs (e.g., *7*).

Among the different model components of an ABM system, the transferability of activity/travel generation components is of particular interest. Since activity/travel generation is modeled at either person-level or household-level, the amount of data available for such models can, sometimes, be smaller compared to the data available for tour-level and trip-level models. At the same time, as discussed in Sikder et al. (*1*), existing empirical evidence suggests the possibility that activity/travel generation model components might be more transferable than those for other travel choices (e.g., mode choice, destination choice). This is perhaps due to a comparatively lower dependency of individuals' daily activity and travel generation on the spatial structures and transport system characteristics of their regions. Further, empirical studies (e.g., *8*) suggest notable similarities in activity participation and time-use patterns across a variety of geographical contexts. However, there is a dearth of empirical evidence on the transferability of activity/travel generation model components used in ABMs.

Among the different approaches to model activity/travel generation, time-use based approaches are of particular interest. This is because a fundamental tenet of the activity-based approach is to view individuals' activity-travel patterns as a result of their time-use decisions. With a given amount of time (e.g., 24 hours in a day), individuals decide how to allocate the time to different activities subject to their socio-demographic, spatio-temporal, and other constraints and opportunities. Motivated by the theoretical strength of the time-use based approaches, significant methodological developments have occurred in the recent past on modeling individuals' activity participation and time-use patterns. Notable among those is the development of the multiple discrete-continuous extreme value (MDCEV) model (*9*), which has now been used in a large number of activity participation and time-use studies (e.g., *10*). The MDCEV structure is now at the heart of a household-level activity generation model component of an activity-based model system being developed in the South California region (*11*).

2 CURRENT RESEARCH

In view of the above discussion, this study aims to provide an empirical assessment of the spatial transferability of person-level daily out-of-home activity generation and time-use models. The geographical contexts of interest in this study are different regions in the State of Florida. Since Florida is considering different options (e.g., develop new models vs. transfer models) to develop ABMs in the state, the results from this study will be of potential use. In addition, the study investigated model transferability between two different states – California (CA) and Florida (FL). This provides an opportunity to compare the extent of transferability between different states (inter-state transferability) to that across different regions of a state (intra-state transferability). The demographic segment of focus in the paper is unemployed adults (age >18).

The econometric model structure used to model activity participation and time-use is the MDCEV model. Since this is the first empirical study of the transferability of an MDCEV-based model, some effort was devoted to understanding the prediction properties of the MDCEV model. This helped shed new light on the prediction properties of the MDCEV model that will have implications to model transferability.

The simplest approach to transfer a model is called the naïve transfer, where the specification and parameter estimates of a model developed in one context (*estimation context*) are directly used in another context (*application context*) without any modifications. The other approaches used in the literature are updating constants, transfer scaling, Bayesian updating, combined transfer estimation, and joint context estimation. In this study, we focus on naïve transfer and updating constants. In the updating constants approach, the specification and all parameter estimates other than constants are directly transferred from the estimation context to the application context; only the constants are estimated using the application context data, while fixing the other parameters as those from the estimation context.

Different metrics have been used in the literature to assess model transferability. These can be broadly categorized as: (1) Statistical tests of model equivalence, (2) Aggregate-level predictive accuracy metrics, and (3) Policy prediction performance. This study uses at least one metric from each category.

The next section provides an overview of the data used in the study. Section 4 discusses the MDCEV model structure and its prediction properties. Section 5 summarizes the empirical model estimation results. Section 6 presents and discusses the transferability assessment results. Section 7 concludes the paper.

3 DATA

The primary data source used for the analysis is the 2009 National Household Travel Survey (NHTS) for the states of California and Florida. For all unemployed adults (age >18) in the data, their weekday daily travel information was used to define eight out-of-home (OH) activities: (1) Shopping (Shop), (2) Other maintenance, such as buy services, gas, etc. (Maintenance), (3) Social/recreational (Soc rec.), (4) Active recreation, such as go to gym, exercise, and play sports (Active rec), (5) Medical, (6) Eat out, (7) Pick up/drop off (pickup/drop), and (8) other activities. For each individual, the daily time-allocation to each of these activity categories was calculated by aggregating the "dwell time" at the destination of each trip made for that activity purpose. The time spent in in-home (IH) activities was computed as total time in a day (24 hours) minus the time allocated to the above out-of-home activities, sleep time (assumed 8.7 hours, as computed from the 2010 American Time Use Survey data), and travel time.

3.1 Geographical Regions Considered for Transferability Assessment

For intra-state transferability assessment, the state of Florida was divided into seven geographical regions based on existing travel demand modeling regions in the state. These are: (1) Southeast Florida (SEF), (2) Central Florida (CF), (3) Tampa Bay (TB), (4) Northeast Florida (NEF), (5) Urban areas in district1 (D1U), (6) Urban areas in district3 (D3U), and (7) Rural Florida. Two of the seven regions (D3U and NEF) were not included in the analysis because of small sample sizes. Of the remaining 5 regions, SEF, CF, and TB include some of the major urban regions in Florida (Miami, Orlando, and Tampa), while D1U comprises counties that are less urbanized compared to the major urban regions and Rural Florida includes all rural counties in Florida with low population and employment densities. Models were transferred only from three regions (SEF, CF, and TB) to all other 5 regions (SEF, CF, TB, DIU, and R). Lower sample sizes of DIU and Rural regions played a role in the decision to not transfer from these regions. At the same time, the state of Florida is considering options for transferring models to D1U and Rural locations, while the major urban regions are moving ahead with the development of their own activity-based models. For inter-state transferability assessment, the entire data in the state of Florida was used to construct the Florida (FL) model and likewise for the California (CA) model.

3.2 Sample Description

Table 1 presents descriptive information about the data used in the analysis, with the first row presenting the sample sizes for different geographies considered in the study. It can be observed that the aggregate-level differences in the demographic characteristics are greater across the two states (CA and FL) than those across different regions within Florida. For example, the proportion of unemployed elderly (age > 65) in Florida (65%) is considerably higher than that in California (53.0%). Greater proportions of whites, less educated individuals, and lower income levels are also observed in Florida than in California. The different regions within Florida are more similar in the demographic makeup, except a few exceptions (noted in bold font) such as greater proportion of non-whites in the Southeast (Miami) region, greater proportion of elderly in D1U region, and greater proportions of lower education and income levels in rural Florida.

In the context of activity participation rates (percentage of individuals participating in each activity) and average daily time allocation, one can observe considerable differences between the non-workers in California and Florida. Specifically, individuals in Florida exhibit higher participation rates in different activities but lower time allocations (than those in CA). This is probably because those in Florida participle in greater number of OH activities per day than those in California (as shown in the last row). Within different regions of Florida, the differences in the aggregate activity participation rates and time allocations are not as much different (as those across the two states). Of course, a few exceptions (noted in bold font) are notable - the activity participation and time allocation to active recreation is significantly lower in rural Florida.

In summary, unemployed adults in California appear to be significantly different from those in Florida in terms of socio-demographic characteristics, activity participation and time-use patterns. The differences across different regions within Florida appear to be smaller, although rural locations display some notable differences than other locations. Though the descriptive statistics cannot shed full light on the transferability of a time-use model from region to another, the noted differences may, in part, have a bearing.

4 PREDICTION PROPERTIES OF THE MDCEV MODEL

The MDCEV model estimated in this study is based on the following utility form (*9*):

$$U(\mathbf{t}) = \psi_1 \ln(t_1) + \sum_{k=2}^{K} \gamma_k \psi_k \ln\left((t_k / \gamma_k) + 1\right) \qquad (1)$$

In the above function, $U(\mathbf{t})$ is the total utility derived by an individual from his/her daily time-use. It is the sum of sub-utilities derived from allocating time (t_k) to each of the activity types *k* (*k =1,2,…,K*). ψ_k , labelled the baseline utility for alternative *k*, is the marginal utility of time allocation to activity *k* at the point of zero time allocation. Between two alternative activities, the activity with greater baseline marginal utility is more likely to be participated (or chosen). γ_k accommodates corner solutions (i.e., possibility of not choosing an alternative) and differential satiation (diminishing marginal utility with increasing consumption) effects for different activity types. The 1st alternative, designated as in-home activity, doesn't have a γ_k parameter since all individuals in the data participate in the in-home activity (i.e., there is no need of corner solutions for this activity).

The influence of observed and unobserved individual characteristics and activity-travel environment (ATE) measures are accommodated as $\psi_1 = \exp(\varepsilon_1)$; $\psi_k = \exp(\beta' z_k + \varepsilon_k)$; and $\gamma_k = \exp(\theta' w_k)$; where, z_k and w_k are observed socio-demographic and ATE measures influencing the choice of and time allocation to activity *k*, β and θ are corresponding parameter vectors, and ε_k (*k=1,2,…,K*) is the random error term in the sub-utility of activity type *k*. The model is derived based on the assumptions that: (1) individuals choose their daily time-use patterns to maximize the total utility subject to a time budget constraint $T = \sum_{t=1 \text{ to } K} t_k$ (*T* is a known amount of time budget available to the individual), and (2) the random error terms ε_k (*k=1,2,…,K*) follow the independent and identically distributed (iid) standard Gumbel distribution with unit scale parameter.

Table 2 presents the prediction results of the models estimated for the 5 regions in Florida (the predictions of the two state-wide models are not presented to save space). For each region, the prediction was performed on its own estimation sample. All the predictions in this paper were performed using the MDCEV forecasting algorithm proposed by Pinjari and Bhat (*12*), using 100 sets of random draws to cover the error term distributions for each individual in the data.

The first set of rows present the predicted (and observed) aggregate shares of individuals participating in each activity type (i.e., the discrete choice component) and the average daily time allocation (or duration) to each activity. The predicted aggregate shares for each activity were computed as the proportion of the instances the activity was predicted with a positive time allocation across all 100 sets of random draws for all individuals. The predicted average duration for an activity was computed as the average of the predicted duration (or time allocation) across all random draws for all individuals. It can be observed that the MDCEV models for all 5 regions perform well in predicting the aggregate shares of participation in each type of activity (i.e., the discrete choice of each alternative). In fact, we noticed that a constants only model resulted in the predicted discrete choice shares same as the observed shares. These results suggest the existence of a fundamental property of the MDCEV model similar to that of the multinomial logit (MNL) model that a constants only model, when applied to the estimation data, would yield the same discrete choice shares as observed in the data. It is difficult to prove this property analytically, because there is no analytical expression to derive the probabilities of discrete choices from the MDCEV model. But additional prediction exercises with other datasets resulted in the same findings, reinforcing our belief on the existence of this property. The property has implications to the transferability of models with MDCEV structure. Specifically, an MDCEV model transferred from elsewhere can simply be adjusted by updating the constants using data from the application context to help improve its prediction of the aggregate discrete choice shares.

In the context of aggregate time allocation to each activity type (i.e., the continuous choice component), the model is under-predicting the time allocation to in-home activities and over-predicting the time allocation to all out-of-home activities except active recreation. A plausible reason behind this discrepancy between the predicted and observed aggregate durations is the asymmetry and the *fat right tail* of the Gumbel distribution used in the MDCEV model. That is, there is a non-negligible chance that the ψ_k values become quite large and therefore lead to unrealistically large time allocations for several choice alternatives. Given the asymmetry of the Gumbel distribution, if large durations are predicted even for a few instances over a large number of error draws, the average of the predicted durations becomes quite large. In addition, whenever a large positive number is drawn for the error term of an out-of-home activity, the alternative hogs up a large amount of the time budget leaving less time for the in-home activity. Further research is warranted to delve deeper into this issue and explore alternative (to Gumbel) distributional assumptions that can help overcome this problem.

5 EMPIRICAL MODEL ESTIMATES

The MDCEV time-use model was estimated for all seven geographies. Considering the word limit, the model estimation results are not provided in the paper but available from the authors. Overall, the parameter estimates have intuitive interpretations and identical signs in all the models. The same factors were often found to influence the time-use choices across all geographies. It is worth noting that the baseline utility constants for the out-of-home activities in the CA model were larger in magnitude (with –ve signs) than those in the Florida models, since the out-of-home activity participation rates in California were lower than that in Florida. Further, the constants in the satiation parameters of the California model were larger (with +ve sign) than those in the Florida models, since the average time allocation to out-of-home activities by Californians (if they participate in the activity) was greater than that by Floridians. The differences in the model constants as well as other parameter estimates within the different regions of Florida were not as high as compared to those across the two states. To the extent that the scale of unobserved factors influencing choices across the different regions are similar, the differences in the model coefficients suggest that models may be better transferable within a state than across states that are as different as California and Florida.

6 TRANSFERABILITY ASSESSMENT

To assess inter-state transferability, the model estimated for California was transferred to Florida and vice-versa. For intra-state transferability assessment, the model estimated for each of the three major urban regions (SEF, CF, and TB) was transferred to the other four regions in Florida (including D1urban and rural regions). Thus, 14 different transfers were performed (2 inter-state transfers and 12 intra-state transfers) for each of the two transfer methods - naïve transfer and updating constants (28 transfers in all).

6.1 Transferability Test Statistic (TTS)

Transferability test statistic (TTS) is used to test the hypothesis that the transferred model is statistically equivalent to a model estimated in the application context (*13*).

$$TTS = -2[L_j(\beta_i) - L_j(\beta_j)] \qquad (3)$$

where, $L_j(\beta_i)$ = log-likelihood of the transferred model applied to the application context data, and $L_j(\beta_j)$ = log-likelihood of the locally estimated model using data from the application context. Although not reported in the tables, for no single transfer was the TTS value lower than the critical chi square value even at the 90% confidence level. These results echo the well-established finding that statistically rigorous tests usually reject model transferability (e.g., *14*). However, rejection by a statistical test does not necessarily mean the poor prediction or forecasting ability of a model. Since the end-objective of a model is for use in prediction and policy analysis, several other measures are used for transferability assessment, as discussed next.

6.2 Log-likelihood-based Measure: Transfer Index (TI)

Transfer index (TI), first used by Koppelman and Wilmot (*15*), measures the degree to which the log-likelihood of a transferred model exceeds that of a reference model (e.g., constants only model) relative to a model estimated in the application context.

$$TI_j(\beta_i) = \frac{L_j(\beta_i) - L_j(\beta_{reference,j})}{L_j(\beta_j) - L_j(\beta_{reference,j})} \quad \text{....................}(4)$$

where, $L_j(\beta_i)$ and $L_j(\beta_j)$ are the same as defined earlier and $L_j(\beta_{reference,j})$ is the log-likelihood of a reference model in the application context. The closer the value of TI is to 1, the closer is the transferred models' performance to a locally estimated model (in terms of the information captured). The upper bound of this index is 1 unless the transferred model performs better than the locally estimated model.

From Table 3, one can observe that the TI values for inter-state naïve transfers are rather poor with negative values (-0.67 and -1.67), suggesting that the transferred models perform worse than locally estimated constants only models. For intra-state naïve transfers within Florida, the TI values range from -0.11 to 0.59 with greater values for transfers between major urban regions (SEF, CF, and TB) and lower values for transfers from these three urban regions to D1U and rural region. The highest TI values can be noted for the models transferred between the SEF and CF regions. Of course, the TI values for transfers from region to another are not the same as those for transfers in the other direction, suggesting that transferability is asymmetric.

After updating the model constants with the application context data, the TI values improved in all cases. Most previous studies (e.g., *16*) found this result in the context of the MNL model. These results suggest that the MDCEV model structure also lends itself to improved TI values (hence improved performance) after updating constants using data from the application context. This is probably due to the property discussed in Section 2. There was a significant improvement in the TI value for the inter-state transfers and considerable improvement for intra-state transfers. Even among intra-state transfers, the percentage improvement in TI value after updating constants is greater for those transfers with low initial TI value. In fact, the models with rather poor TI values (-ve values) for naïve transfer were the ones with the most improved TI values after updating constants.

6.3 Aggregate-level Predictive Accuracy

To assess the aggregate-level predictions of a transferred model, two metrics were used: (1) Root mean square error (RMSE) and (2) Relative Aggregate Transfer Error (RATE).

RMSE measures the aggregate-level predictive ability of a model against aggregate observed patterns in the data.

$$RMSE = \left(\frac{\sum_k P_k \times REM_k^2}{\sum_k P_k} \right)^{1/2} \quad \text{....................(5)}$$

where, P_k and O_k are the aggregate predicted and observed shares (or durations averaged over all individuals), respectively for alternative k, and $REM_k = \frac{P_k - O_k}{O_k}$ is the percentage error in the prediction of alternative *k*. RATE is a relative measure; it measures the aggregate predictive ability of the transferred model relative to that of a locally estimated model.

$$RATE = \frac{RMSE_j(\beta_i)}{RMSE_j(\beta_j)} \text{....................(6)} .$$

Table 4 reports the RMSE and RATE values for all the transfers conducted in the study. As expected, the aggregate errors of the locally estimated models (in bold) are lower than those of transferred models.

For naïve transfers, the RATEs for inter-state transfers are higher than those for intra-state transfers, suggesting that model transfers across the states can result in poorer aggregate predictions than transfers within the state. This is consistent with the findings in the context of TI. Among intra-state naïve transfers, the RATEs are higher for transfers from urban to rural locations (ranging from 1.48 to 4.00) than those for urban-urban transfers (ranging from 1.00 to 2.33), suggesting greater transferability from urban regions to urban regions than to a rural region. The lowest aggregate relative errors can be observed for these transfers: SEF→CF, CF→TB, and CF→SEF.

After updating the constants of the transferred models, there is significant improvement in the RMSE values. In most cases, regardless of how poor the naïve transfer performance was, the aggregate prediction errors from transferred models drop to the level of the errors from the corresponding locally estimated model (bringing down the RATE value close to or equal to 1). These results suggest that, similar to previous findings in the context of MNL models (*16*), updating the constants of a transferred MDCEV model can help in improving its aggregate prediction performance to that of a locally estimated model. Recall that similar results were found in the context of transfer index as well; with significant improvements in the TI values after updating the constants of poorly performing naïve transfers. But intuition suggests that if the naïvely transferred model performs rather poorly, simply updating the model constants doesn't do the *magic* of getting things right. As discussed in Section 2, it is the property of the MDCEV model structure that updating its constants helps improve the aggregate-level predictions, rather than an improvement in the way the model captures behavior in the application context. To examine this, the next subsection presents transferability assessment based on the ability of the transferred models to forecast changes in activity time-use patterns in response to changes in explanatory variables.

6.4 Policy Response Measures

To assess model transferability based on how the models respond to changes in explanatory variables, we used a policy scenario where the age of individuals older than 29 years was increased by 10 years (to reflect aging of the population). Next, each estimated model was applied to its estimation sample and all the application context datasets (to which the model was transferred) for both base and policy scenarios. The changes in the time-use patterns (due to the policy) were computed at two levels – disaggregate and aggregate.

At the disaggregate-level, first, for each set of error term draws for each individual, the overall change in activity participation and time-use patterns was measured as below.

$$T_c = \frac{1}{T}\left(\sum_{k=1}^{K} \frac{|\hat{t}_k^{\,p} - \hat{t}_k^{\,b}|}{2}\right) \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

where, $\hat{t}_k^{\,p}$ is the predicted duration for alternative k in the policy case, and $\hat{t}_k^{\,b}$ = predicted duration for alternative k in the base case. Next, the above metric was averaged over all sets of error term draws for all individuals.

The aggregate-level policy assessment metric is defined as the total absolute change in predicted shares for all choice alternatives: $\sum_{k=1}^{K}\left|\hat{p}_k^{\,p} - \hat{p}_k^{\,b}\right|$, where $\hat{p}_k^{\,p}$ and $\hat{p}_k^{\,b}$ are the predicted aggregate shares for alternative *k* in the policy and base case scenarios, respectively. This metric focuses on the discrete (activity participation) component of choice.

Table 5 presents the above-discussed metrics, with the values outside the parentheses indicating the predicted policy response by the transferred model, and the values inside the parentheses indicating the ratio of the same metric with respect to that of a locally estimated model. The closer the values in the parenthesis are to 1, the closer is the transferred model's policy response prediction to the corresponding locally estimated model, and therefore, better transferability. These results suggest that for both inter-state and intra-state transfers, updating constants does not help much in improving the performance of the transferred model (i.e., in predicting the policy changes closely to that from a locally estimated model). In some cases, it rather seems to deteriorate the performance of the transferred model. These results are quite in contrast to the findings from the log-likelihood based (TI) and aggregate prediction-based (RMSE and RATE) metrics. While updating constants has been found to provide significant improvement in the TI values and aggregate-level prediction (as in many studies), the results here suggest that such improvements do not necessarily translate to improvement in the policy responses of the transferred model.

6.5 Overall Assessment

Table 6 presents a summary of the results (for transfers within Florida) from all the transferability assessment metrics used in the study except TTS (the TTS anyway rejects the hypothesis of transferability in all cases). To gain a better perspective from the results, we define four levels of transferability based on the error in the performance of a transferred model in the application context (for details, see the notes below Table 6). For each model transferred, the *level* of transferability (1, 2, 3, or 4) is denoted as the superscript for the region where the model was transferred from. Also, following Nowrouzian and Srinivasan (*7*), for each application context, the various transferred models are arranged in the descending order of transferability defined by the above scheme of categorization in to 4 different *levels*. For example, based on transfer index for naïve transfers, the transferability to rural region of the SEF model is similar to that of the CF model (similarity denoted by "~") but better than (">") that of the TB model. Of course, the levels are defined based on arbitrarily defined thresholds, but the analyst has to determine the *acceptable error thresholds* to draw broad conclusions on transferability.

The RATEs suggest that, regardless of the level of transferability of a naively transferred model, any transferred model can be improved (to transferability level 1) by simply updating its constants. However, as discussed earlier and can be observed from the last two sets of rows, this improvement doesn't translate to improvement in the level of transferability in terms of the ability to provide appropriate policy predictions. Recall that the TI values also improved after updating constants, but the improvement for intra-state transfers was not sufficient enough to enable jumps in the *level* of transferability unless the naïve transfer had a rather low TI value. The takeaway point here is that updating model constants can help with predicting the observed aggregate activity participation and time-use patterns closely, but not necessarily in predicting appropriate policy responses. Since updating model constants is a widely used practice to transfer models, it is important for model-developers and model-users to be cognizant of this issue.

For any application context, the order of transferability of different transferred models does not change (or it doesn't get reversed) after updating constants. However, the order seems to vary by the metric used to assess transferability – specifically between the aggregate prediction metrics (RATE) and the disaggregate metrics such as TI and policy responses.

There is greater correlation between the inferences from TI and policy response-based assessment, where as inferences from the aggregate prediction-based metrics tally less with those from other metrics. For instance, both TI and policy assessments imply almost similar order of transferability of different models (for any application context). Similarly, although TI values improved after updating constants, neither TI nor policy assessments suggested significant improvement in transferability after updating model constants (except that TI showed significant improvement if the naïve transfer has a poor TI value). These findings suggest that greater TI value of a naively transferred model is likely to imply better policy response of that model, but better neither aggregate prediction of observed patterns nor improvements in the TI after updating constants necessarily imply better policy prediction. Thus, future policy response assessments should place greater emphasis on log-likelihood based metrics (before updating constants) and even greater emphasis on policy response measures.

Finally, the transferability from urban region models to D1U and Rural regions seems to be much lower than transferability between the three major urban region models (SEF, CF, TB). Further, the SEF and CF models are more transferable to other regions in Florida than the TB model.

7 SUMMARY AND CONCLUSIONS

This paper presents an empirical assessment of the spatial transferability of person-level activity generation and time-use models among different regions in Florida (intra-state transferability) and between Florida and California (inter-state transferability). The empirical models are for unemployed adults based on the multiple discrete-continuous extreme (MDCEV) structure. An examination of the prediction properties of the MDCEV model is provided first, followed by an assessment of transferability for two approaches to transferring models – (1) Naïve transfer, and (2) Updating model constants. Transferability is evaluated using different measures such as log-likelihood based measures, aggregate predictive ability, and model sensitivity to changes in demographic characteristics.

The results shed new light on the prediction properties of the MDCEV model that has implications to transferability, as well as provide insights into how the model can be improved. First, similar to the multinomial logit model, the MDCEV model estimated with only constants, when applied to the estimation data, appears to provide accurate aggregate shares of the choice of discrete alternatives. This property has implications to model transferability. Specifically, updating the constants of a transferred MDCEV model using data from the application context can help improve its aggregate-level discrete choice predictions. Second, the MDCEV model appears to under-predict the continuous quantity dimension of choice (activity durations, in the current context) for certain choice alternatives (in-home activity) while it over-predicts for other alternatives (most of the out-of-home activities). A closer examination of the predictions suggested that the asymmetry and the fat right tail of the Gumbel distributions assumed in MDCEV is a possible cause, suggesting the need to explore alternative (to Gumbel) distributional assumptions for MDC models.

The transferability assessment revealed several findings. First, the ability to predict aggregate observed patterns is not an adequate measure of transferability. Greater emphasis should be placed on disaggregate-level prediction metrics and more importantly policy prediction ability. Similar findings were reported in Karasmaa (*17*) and Nowrouzian and Srinivasan (*7*). Second, updating the constants of a transferred MDCEV model can significantly improve its ability to predict aggregate shares in the context to which it is transferred. But this does not necessarily translate into an improvement in the transferred model's ability to provide appropriate sensitivities to changes in demographic characteristics and other variables. While these results do not argue against updating the model constants, it is important that the transferred model must exhibit a minimum level of performance without any updates. Only then does it make sense to update its constants. Thus, empirical research should be more focused on the development of more transferable models by better capturing the behavior than directly utilizing updating methods that simply rely on the mechanics (or mathematical properties) of the model to match aggregate predictions. Third, the extent of transferability between different regions within a state is greater than that across different states. Thus, whenever possible, attempts should be made to transfer models within a state. Within Florida, the transferability between urban regions is greater than that from urban to rural region. Specifically, there appears to be greater transferability of time-use models between the Southeast Florida and the Central Florida regions.

The current study can be extended in several ways. First, for inter-state transferability assessment, only the models developed at the state-level were considered. It would be useful to investigate transferability between specific regions of the two states with similar characteristics (e.g., specific urban regions). Second, the scale of the random utility components was assumed to be similar across different models. Allowing for scale differences across different regions can potentially shed further light on model transferability. Third, all the findings in the current study are based on *relative* transferability assessments. In an *absolute* sense, we wouldn't declare the transferability of the empirical activity time-use models estimated in this study as unequivocally acceptable. Significant improvements can be made to the model specification to enhance transferability, provided additional data becomes available on the activity-travel environment and accessibility to different activities. Finally, additional empirical assessments are warranted to corroborate the conclusions from this study.

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LIST OF TABLES

TABLE 1 Descriptive Statistics of Socio-demographics, Activity Participation and Time Allocation in the Datasets

	California (CA)	**Florida (FL)**	**SEF**	**CF**	**TB**	**D1U**	**R**
Sample Size	10, 821	8,396	2,088	1,458	1,334	995	757
Socio-demographic Characteristics							
Male	40.0%	41.8%	41.4%	42.2%	42.6%	42.9%	43.9%
Age: 18 - 29 years	7.8%	3.1%	3.4%	2.5%	2.5%	3.1%	3.2%
Age: 30 - 64 years	39.2%	31.9%	29.0%	33.3%	32.8%	26.5%	34.1%
Age: ≥65 years	**53.0%**	**65.0%**	67.7%	64.1%	64.6%	**70.4%**	62.7%
Race: White	**78.6%**	**89.8%**	**84.1%**	92.0%	93.0%	94.9%	91.0%
Race: Black	3.7%	5.6%	7.9%	3.9%	3.7%	2.3%	5.0%
Race: Other	17.7%	4.6%	8.0%	4.1%	3.4%	2.8%	4.0%
Driver	85.5%	87.1%	82.7%	90.1%	86.5%	90.4%	87.6%
Edu.: H.school/low	**35.6%**	**44.0%**	39.8%	42.2%	45.2%	43.2%	**57.2%**
Edu.:Some College	31.7%	27.5%	26.7%	29.1%	27.6%	27.9%	25.6%
Edu.:Bach./higher	32.7%	28.4%	33.5%	28.7%	27.2%	28.8%	17.2%
Income: <25 K	23.4%	29.3%	29.9%	29.0%	31.7%	**23.2%**	**37.6%**
Income: 25-75K	46.1%	49.4%	46.3%	51.1%	49.9%	52.9%	51.0%
Income: > 75 K	**30.5%**	**21.4%**	23.7%	20.0%	18.4%	23.9%	11.4%
Avg. HH Size	2.5	2.2	2.1	2.1	2.0	2.1	2.1
Avg. No. of Drivers	1.8	1.8	1.7	1.7	1.6	1.7	1.7

Aggregate Activity Participation (% who participated) and Average Duration (among those who participated)

Activity Types	CA % Part.	CA Duration	FL % Part.	FL Duration	SEF % Part.	SEF Duration	CF % Part.	CF Duration	TB % Part.	TB Duration	D1U % Part.	D1U Duration	R % Part.	R Duration
In-home activities	100.0	743.4	100.0	740.3	100.0	**729.2**	100.0	741.1	100.0	744.2	100.0	**729.7**	100.0	748.4
OH-Shopping	**42.9**	59.7	**48.4**	55.1	51.0	56.0	49.9	56.5	48.5	51.5	51.0	54.6	48.1	50.3
OH-Other Main.	**24.2**	56.7	**29.6**	50.3	30.6	**56.54**	30.4	44.4	31.6	45.2	30.7	47.0	30.1	46.6
OH-Soc./Rec.	**23.1**	**157.3**	**29.2**	**126.9**	30.5	129.1	30.0	**117.5**	27.1	131.4	31.3	**119.8**	28.9	130.3
OH-Active Rec.	**14.1**	**83.9**	**20.2**	**52.9**	20.6	49.9	21.9	52.9	21.2	52.0	24.6	**61.9**	14.7	**29.3**
OH-Medical	**12.7**	**80.9**	**22.5**	**60.4**	24.8	**67.4**	24.3	50.7	23.4	57.5	24.8	58.6	19.8	**65.9**
OH-Eat out	**19.4**	**61.6**	**24.9**	**48.5**	24.3	47.6	27.2	48.7	24.4	45.5	28.0	50.3	23.8	48.2
OH-Pick/Drop	**13.3**	17.9	**15.2**	15.9	17.0	16.8	16.2	13.6	15.5	16.3	16.0	12.5	12.8	16.5
OH-Other activities	**7.8**	34.7	**6.1**	22.2	5.7	**28.3**	5.7	14.8	7.0	18.1	5.0	20.5	7.5	16.2
Avg. No. OH activities	**1.6**		**2.0**		2.0		2.1		2.0		2.1		1.9	

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

TABLE 2 Predicted and Observed Activity Participation (% participation) and Duration[1]

Predicted and Observed Activity Participation & Duration in individual activities										
		In-home	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Eat Out	Pick Up/ Drop Off	Other Activities
SEF	% Participation	100.0 (100.0)	49.2 (51.0)	29.9 (30.6)	29.0 (30.5)	19.1 (20.6)	23.1 (24.8)	22.8 (24.3)	16.0 (17.0)	5.3 (5.7)
	Avg. Duration	688.0 (729.2)	45.4 (28.5)	24.9 (17.1)	48.9 (39.4)	6.7 (10.3)	20.3 (16.7)	17.3 (11.6)	3.7 (2.9)	2.1 (1.6)
CF	% Participation	100.0 (100.0)	49.3 (49.9)	30.9 (30.4)	29.1 (30.0)	20.4 (21.9)	23.0 (24.3)	26.2 (27.2)	15.5 (16.2)	5.3 (5.7)
	Avg. Duration	697.0 (741.1)	45.6 (28.2)	22.1(13.5)	43.9 (35.2)	6.8 (11.6)	17.1 (12.3)	20.6 (13.2)	3.5 (2.2)	1.5 (0.8)
TB	% Participation	100.0 (100.0)	47.9 (48.5)	31.9 (31.6)	26.3 (27.1)	19.6 (21.2)	22.4 (23.4)	23.6 (24.4)	14.4 (15.5)	6.6 (7.0)
	Avg. Duration	701.4 (744.2)	42.4 (25.0)	22.6 (14.3)	44.2 (35.6)	6.8 (11.0)	17.3 (13.4)	18.1 (11.1)	3.6 (2.5)	2.1 (1.3)
D1U	% Participation	100.0 (100.0)	48.3 (51.0)	30.5 (30.7)	30.1 (31.3)	22.7 (24.6)	22.9 (24.8)	26.6 (28.0)	15.1 (16.0)	4.6 (5.0)
	Avg. Duration	688.4 (729.7)	44.3 (27.8)	22.5 (14.4)	46.9 (37.4)	10.1 (15.2)	17.9 (14.5)	21.5 (14.1)	3.0 (2.0)	1.6 (1.0)
R	% Participation	100.0 (100.0)	47.9 (48.1)	30.7 (30.1)	29.0 (28.9)	14.1 (14.7)	19.1 (19.8)	23.0 (23.8)	12.1 (12.8)	7.2 (7.5)
	Avg. Duration	706.0 (748.4)	40.4 (24.2)	20.0 (14.0)	48.0 (37.7)	2.7 (4.3)	15.3 (13.1)	18.6 (11.5)	2.9 (2.1)	2.5 (1.2)

[1] Observed shares and durations are in the parentheses

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

TABLE 3 Transferability Assessment Results: Transfer Index (TI)

Inter-state Transfer

Transferred From \ Transferred To	California		Florida	
	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
California	**1.00**	**1.00**	-1.67	0.80
Florida	-0.67	0.86	**1.00**	**1.00**

Intra-state Transfer

Transferred From \ Transferred To	SEF		CF		TB		D1U		R	
	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
SEF	**1.00**	**1.00**	0.53	0.68	0.26	0.59	0.20	0.38	0.12	0.66
CF	0.59	0.70	**1.00**	**1.00**	0.46	0.64	0.17	0.25	0.15	0.76
TB	0.29	0.41	0.28	0.41	**1.00**	**1.00**	-0.06	0.17	-0.11	0.30

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

TABLE 4 Transferability Assessment Results: Root Mean Square Error (RMSE) & Relative Aggregate Transfer Error (RATE)

Inter-state Transfer

	Transferred To / Transferred From	California		Florida	
		Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Discrete Component	California	**0.07 (1.00)**	**0.07 (1.00)**	0.23(5.75)	0.04 (1.00)
Discrete Component	Florida	0.25 (3.35)	0.07 (1.00)	**0.04 (1.00)**	**0.04 (1.00)**
Continuous Component	California	**0.17 (1.00)**	**0.17 (1.00)**	0.33 (1.57)	0.21 (1.00)
Continuous Component	Florida	0.24 (1.41)	0.17 (1.00)	**0.21 (1.00)**	**0.21 (1.00)**

Intra-state Transfer

	Transferred To / Transferred From	SEF		CF		TB		D1U		R	
		Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Discrete Component	SEF	**0.03(1.00)**	**0.03(1.00)**	0.04(1.00)	0.04(1.00)	0.07(2.33)	0.03(1.00)	0.06(1.50)	0.04(1.00)	0.08(4.00)	0.03 (1.50)
Discrete Component	CF	0.04(1.33)	0.04(1.33)	**0.04(1.00)**	**0.04(1.00)**	0.04(1.33)	0.04(1.33)	0.04(1.00)	0.04(1.00)	0.06(3.00)	0.02(1.00)
Discrete Component	TB	0.05(1.67)	0.03(1.00)	0.06(1.50)	0.04(1.00)	**0.03(1.00)**	**0.03(1.00)**	0.08(2.00)	0.04(1.00)	0.06(3.00)	0.02(1.00)
Continuous Component	SEF	**0.11(1.00)**	**0.11(1.00)**	0.31(1.94)	0.16(1.00)	0.31(1.80)	0.18(1.05)	0.28(2.13)	0.15(1.15)	0.22(2.00)	0.10 (0.90)
Continuous Component	CF	0.16(1.41)	0.14(1.20)	**0.16(1.00)**	**0.16(1.00)**	0.18(1.05)	0.17(1.00)	0.15(1.15)	0.15(1.15)	0.18(1.66)	0.16(1.48)
Continuous Component	TB	0.17(1.48)	0.15(1.31)	0.16(1.00)	0.14(0.87)	**0.17(1.00)**	**0.17(1.00)**	0.13(1.00)	0.15(1.15)	0.16(1.48)	0.15(1.39)

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

* The values outside the parentheses indicate absolute RMSE while the values within the parentheses indicate relative RMSE with respect to a locally estimated model (RATE)

TABLE 5 Transferability Assessment Results: Disaggregate and Aggregate Policy Response Measures

Inter-state Transfer

		Transferred To → / Transferred From ↓	California		Florida	
			Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Policy Response	Disaggregate	California	**4.88(1.00)**	**4.88(1.00)**	4.86(1.64)	5.54(1.87)
		Florida	2.46(0.50)	2.57(0.53)	**2.96(1.00)**	**2.96(1.00)**
	Aggregate	California	**4.72(1.00)**	**4.72(1.00)**	4.68(1.31)	6.74(1.88)
		Florida	3.70(0.78)	2.68(0.57)	**3.58(1.00)**	**3.58(1.00)**

Intra-state Transfer

		Transferred To → / Transferred From ↓	SEF		CF		TB		D1U		R	
			Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Policy Response	Disaggregate	SEF	**2.25(1.00)**	**2.25(1.00)**	2.57(1.58)	2.20(1.36)	2.50(0.51)	2.20(0.45)	2.21(0.55)	1.90(0.47)	2.71(2.22)	2.14(1.74)
		CF	1.42(0.63)	1.48(0.66)	**1.62(1.00)**	**1.62(1.00)**	1.50(0.31)	1.33(0.27)	1.37(0.34)	1.37(0.34)	1.65(1.35)	1.51(1.23)
		TB	4.90(2.18)	5.18(2.30)	5.36(3.31)	5.36(3.31)	**4.88(1.00)**	**4.88(1.00)**	5.52(1.36)	5.75(1.42)	5.32(4.35)	5.31(4.34)
	Aggregate	SEF	**3.15 (1.00)**	**3.15(1.00)**	3.42(1.36)	3.24(1.31)	3.33(0.65)	3.15(0.61)	3.24(2.49)	3.06(2.35)	3.69(2.54)	2.88(1.96)
		CF	2.43(0.77)	2.52(0.79)	**2.52(1.00)**	**2.52(1.00)**	2.43(0.47)	1.35(0.26)	2.07(1.60)	2.07(1.60)	2.70(1.84)	2.25(1.52)
		TB	5.31(1.69)	5.49(1.74)	5.94(2.38)	6.12(2.46)	**5.13(1.00)**	**5.13(1.00)**	6.12(4.78)	6.3(4.92)	5.67(3.88)	5.31(3.63)

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

TABLE 6 Overall Transferability Assessment Results

	Transferred To	Transferred From	
		Naïve Transfer	**Updated Constants**
Transfer Index	SEF	$CF^{2} > TB^{3}$	$CF^{2} > TB^{3}$
	CF	$SEF^{2} > TB^{3}$	$SEF^{2} > TB^{3}$
	TB	$SEF^{3} \sim CF^{3}$	$SEF^{2} \sim CF^{2}$
	D1U	$SEF^{3} \sim CF^{3} > TB^{4}$	$SEF^{3} \sim CF^{3} \sim TB^{3}$
	R	$SEF^{3} \sim CF^{3} > TB^{4}$	$CF^{1} > SEF^{2} > TB^{3}$
RATE: Discrete Component	SEF	$CF^{2} > TB^{3}$	$CF^{2} > TB^{1}$
	CF	$SEF^{1} >> TB^{3}$	$SEF^{1} \sim TB^{1}$
	TB	$CF^{1} >> SEF^{4}$	$CF^{1} \sim SEF^{1}$
	D1U	$CF^{1} > SEF^{2} > TB^{3}$	$CF^{1} \sim SEF^{1} \sim TB^{1}$
	R	$SEF^{4} \sim CF^{4} \sim TB^{4}$	$SEF^{1} \sim CF^{1} \sim TB^{1}$
RATE: Continuous Component	SEF	$CF^{2} \sim TB^{2}$	$CF^{1} > TB^{2}$
	CF	$TB^{1} >> SEF^{3}$	$TB^{1} \sim SEF^{1}$
	TB	$CF^{1} >> SEF^{3}$	$CF^{1} \sim SEF^{1}$
	D1U	$TB^{1} \sim CF^{1} >> SEF^{4}$	$TB^{1} \sim CF^{1} \sim SEF^{1}$
	R	$TB^{2} > CF^{3} \sim SEF^{3}$	$SEF^{1} > TB^{2} \sim CF^{2}$
Policy Response: Disaggregate Measure	SEF	$CF^{2} >> TB^{4}$	$CF^{2} >> TB^{4}$
	CF	$SEF^{3} > TB^{4}$	$SEF^{2} >> TB^{4}$
	TB	$SEF^{2} > CF^{3}$	$SEF^{3} \sim CF^{3}$
	D1U	$SEF^{2} \sim TB^{2} > CF^{3}$	$TB^{2} > SEF^{3} \sim CF^{3}$
	R	$CF^{2} >> SEF^{4} \sim TB^{4}$	$CF^{1} >> SEF^{3} > TB^{4}$
Policy Response: Aggregate Measure	SEF	$CF^{1} >> TB^{3}$	$CF^{1} >> TB^{3}$
	CF	$SEF^{2} >> TB^{4}$	$SEF^{2} >> TB^{4}$
	TB	$SEF^{2} > CF^{3}$	$SEF^{2} > CF^{3}$
	D1U	$CF^{3} > SEF^{4} \sim TB^{4}$	$CF^{3} > SEF^{4} \sim TB^{4}$
	R	$CF^{3} > SEF^{4} \sim TB^{4}$	$CF^{3} \sim SEF^{3} > TB^{4}$

* Superscripts
  - Level 1: less than 25% error - Transfer Index (0.75 –1.00), RATE (1.00 –1.25), Policy Response Ratio (0.75 –1.00 ~1.00 –1.25)
  - Level 2: 25% - 50% error - Transfer Index (0.50 – 0.74), RATE (1.26 –1.50), Policy Response Ratio (0.50 – 0.74 ~ 1.26 –1.50)
  - Level 3: 50% - 100% error - Transfer Index (0.00 – 0.49), RATE (1.51 –2.00), Policy Response Ratio (0.00 – 0.49 ~ 1.51 –2.00)
  - Level 4: >100% error - Transfer Index (< 0.00), RATE (>2 .00), Policy Response Ratio (>2.00)
* Signs
  - "~" - Transferability of one model is *similar* to that of the other model
  - ">"-Transferability of one model is *better* than that of the other model
  - ">>"-Transferability of one model is *far better* than that of the other model
* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida