Development and estimation of a semi-compensatory model with a flexible error structure

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Abstract

In decisions involving many alternatives, such as residential choice, individuals conduct a two-stage decision process, consisting of eliminating non-viable alternatives and choice from the retained choice set. In light of the potential of semi-compensatory discrete choice models to mathematically represent such decisions, research is inching ahead with the aim of alleviating their high computational complexity and their severe restrictive assumptions. To date, still a major barrier for the implementation of semi-compensatory models is their underlying assumption of independently and identically distributed error terms across alternatives at the choice stage. This study relaxes the assumption by introducing nested substitution patterns and alternatively random taste heterogeneity at the choice stage, thus equating the structural flexibility of semi-compensatory models to their compensatory counterparts. The proposed model is applied to off-campus rental apartment choice by students. Results show the feasibility and importance of introducing a flexible error structure into semi-compensatory models.

Keywords: Semi-compensatory models; two-stage models; flexible error structure; Error Components Logit; Random Coefficients Logit.

1. Introduction

In situations characterized by a large number of alternatives, individuals engage in a semi-compensatory choice process, namely a two-stage process consisting of a sequence of an elimination-based choice set formation and a utility-based choice (Payne et al., 1993). Recent behavioral experiments show the importance of semi-compensatory choice processes in residential location choice (Habib and Miller, 2007; Rashidi et al., 2011), marketing (Chakravarti et al., 2006) and transportation (Hochmair and Rinner, 2005).

The choice outcomes of semi-compensatory choice-processes are typically represented by compensatory choice models due to their estimation ease and their ability to represent similarity patterns across alternatives, taste heterogeneity across individuals and correlations across repeated individual choices. Nevertheless, the fundamental assumption underlying compensatory models, namely utility maximization as sole cognitive mechanism, is behaviorally justified only in choice situations involving a few alternatives (Payne et al., 1993; Shocker et al., 1991). Moreover, neglecting information related to the elimination phase might result in mis-specified choice sets and lead to biased estimates of model parameters, a lack of robustness in parameter estimates, and violations of the independence from irrelevant alternatives assumption (Başar and Bhat, 2004; Chakravarti et al., 2006; Cantillo et al., 2006; Kaplan et al., 2011a).

Semi-compensatory models show promise in embedding the elimination phase and the derived choice set formation as an integral part of discrete choice models. These models represent a probabilistic two-stage choice process consisting of choice set formation upon satisfying random constraints by meeting their respective critical values (thresholds), followed by a utility-maximization based choice (Swait and Ben-Akiva, 1987).

Although the foundations of the semi-compensatory models were laid in the 1970's (Manski, 1977; Payne, 1976), and a few prototypes were developed in the 1980's (Borgers et al., 1986; Gensch, 1987; Swait and Ben-Akiva, 1987), their conceptual and mathematical development has only recently gained momentum and is still in its early stage. In fact, in the last two decades semi-compensatory models are inching ahead with the aim of alleviating their high computational complexity and their severe restrictive assumptions that impede their practical application.

Following the two-stage approach proposed by Manski (1977) and elaborated by Swait and Ben Akiva (1987), several studies, namely Ben-Akiva and Boccara (1995), Morikawa (1995), and Başar and Bhat (2004), mark a breakthrough in terms of mathematical formulation and model estimation with respect to the early prototypes. They also contribute to the conceptual evolvement of random constraints by contemplating utility-related attribute-based thresholds. Cantillo and Ortúzar (2005) and Cantillo et al. (2006) postulate triangular, uniform and normal attribute-based threshold distributions, bivariate correlation across two thresholds, impact of a single individual characteristic, and time effects. Zheng and Guo (2008) depict a single threshold as an ordered-response variable related to a single individual characteristic. Swait (2001a), Martínez et al. (2009) and Castro et al. (2009) take a one-stage approach for embedding the choice set formation into utility-based models, by introducing thresholds as penalties in the utility function. Alternatively, Swait (2001b) treats the two-stage procedure as a cross-nested decision of set and alternative.

Despite the achieved progress, semi-compensatory choice models remain practically limited in three important aspects. First, although applied to real-world situations, all of the aforementioned models are estimated typically for 3-4 alternatives, or alternatively for nine choice sets at most. Second, the number of criteria thresholds and the number determinants that explain their selection are limited. Third, all the models are based on the assumption of independently and identically distributed (i.i.d.) error terms across alternatives in the representation of the utility-based choice.

Kaplan et al. (2011a) propose a semi-compensatory model for residential choice, based on the collection of information regarding threshold selection in addition to choice outcomes. The model is suitable for lifestyle and consumer choices in which thresholds can be overtly specified by individuals (Kaplan et al., 2011b). Kaplan et al. (2009) extend the approach for incorporating correlation across thresholds, while Kaplan and Prato (2010) extend the approach also for habitual decisions, such as route choice, by suggesting a methodology for inferring threshold selection from consideration sets. The approach enables to alleviate the restrictions regarding the number of alternatives and choice sets and enables to refine the representation of threshold selection. In fact, the model is applied to a case-study entailing 400 alternatives and 83 choice sets (Kaplan et al., 2010). The model can depict the selection of multiple independent ordered-response thresholds related to individual characteristics (Kaplan et al., 2011a), correlated ordered-response thresholds (Kaplan et al., 2009), multinomial thresholds (Kaplan et al., 2010) and hazard-based thresholds (Kaplan and Prato, 2010). However, as all other semi-compensatory models, the model remains crippled by assuming i.i.d. error terms across alternatives in the utility-based choice stage.

While the i.i.d. assumption renders the simple and elegant multinomial logit model (MNL), it implies restrictive substitution patterns, it cannot represent random taste heterogeneity, and it cannot be used with panel data (Train, 2009). These limitations are heavily criticized and resolved in the literature of compensatory model by introducing the Generalized Extreme Value (GEV) family (McFadden, 1978), the multinomial probit (e.g., Hausman and Wise, 1978) and the mixed logit (McFadden and Train, 2000). Consequently, the potential of semi-compensatory models has not been fully realized and they remain inferior in comparison with their compensatory counterparts.

The current study extends the models of Kaplan et al. (2009, 2011a) by incorporating a flexible error structure at the utility-based choice stage. The representation of the choice set formation accounts for multiple correlated ordered-response thresholds, while the representation of the utility-based choice accommodates panel data with alternatively nested correlation patterns across the alternatives and random taste heterogeneity across the population. The consideration of a flexible error structure, more than a mere econometric issue, signalizes a change of mind-set towards a wide-spread application of semi-compensatory models, and towards their integration in state-of-the-art activity-based models.

The proposed semi-compensatory model is applied to off-campus rental apartment choice of students. This issue has been scarcely explored, despite the growing role of students in the private rental sector in recent years (Rugg et al., 2002; Charbonneau et al., 2006). The model is particularly suitable in the context of residential choice, due to (i) the recognized importance of elimination-based choice set formation, which matches individual constraints or mental aspirations prior to the choice stage in residential choice (e.g., Borgers et al., 1986; Habib and Miller, 2007; Kaplan et al., 2011a; Rashidi et al., 2011), (ii) the reliance on on-line real-estate internet database search in the rental market (e.g., Habib and Miller, 2007; Kaplan et al., 2011a) that encourage such a two-stage choice process, and (iii) the importance of incorporating correlation patterns across alternatives and random taste heterogeneity in residential choice models (e.g., Chattopadhyay, 2000; Bhat and Guo, 2004; Barrios-Garcıá and Rodriguez-Hernández, 2007).

The remainder of the paper is organized as follows. Section 2 focuses on the formulation of the proposed semi-compensatory model. Section 3 presents the empirical context and provides details regarding the estimation sample. Estimation results are presented in section 4. Last, in section 5, conclusions are drawn, limitations are discussed and further research is recommended.

2. Semi-compensatory model formulation

The framework of the proposed model derives from Manski’s (1977) probabilistic two-stage model:

$$P_q(i|G) = \sum_{S \in G} P_q(i|S) P_q(S|G) \quad (1)$$

where $P_q(i|G)$ is the probability of individual q ($q=1,2,\ldots,Q$) to choose alternative i from the universal realm G of alternatives, $P_q(S|G)$ is the probability of individual q to form a viable choice set S from G at the first stage, and $P_q(i|S)$ is the probability of individual q to choose alternative i out of S at the second stage.

The strength of Manski's (1977) formula is its generality. In particular, the formula does not necessitate any assumption or information regarding the cognitive processes underlying the choice set formation and subsequent choice. The disadvantage however is that the number of theoretically possible choice sets grows exponentially with the number of alternatives and soon becomes unwieldy.

Kaplan et al. (2009, 2011a) managed to alleviate the computational complexity embedded in Manski’s (1977) formula by reducing the number of possible choice sets to those actually chosen, hence avoiding the sum over all the theoretically possible choice sets for model estimation purposes. Accordingly, the choice probability within the proposed framework is expressed as:

$$P_q(i|G) = P_q(i|S) P_q(S|G) \quad (2)$$

The current study assumes a two-stage cognitive process consisting of a sequence of conjunctive heuristic and utility maximization. The conjunctive heuristic is by far the most frequent attribute-based heuristic (Lussier and Olshavsky, 1979; Olshavsky, 1979), while utility maximization is the most prominent model of rational decision making. According to the above assumption, at the first stage of the two-stage process individuals overtly specify their tolerated criteria threshold values concerning acceptable price and quality to delimit the universal realm of alternatives to a viable choice set. At the second stage of the two-stage process, individuals choose their preferred alternative from their retained choice set. In the case that some individuals do not find their ideal alternative within their retained choice set, they may select the most preferred available alternative, update their criteria thresholds, or decide not to choose and thus reveal the need for market expansion. The two-stage process, which is illustrated in figure 1, largely agrees with the behavioral two-stage choice process described by Habib and Miller (2007) and Rashidi et al. (2011).

[Insert Figure 1 about here]

2.1 Choice set formation stage: conjunctive heuristic with correlated thresholds

Assuming that individuals apply a conjunctive heuristic to form their viable choice set, the choice-set selection probability $P_q(S|G)$ derives from the probability to select a combination of criteria thresholds representing individual constraints.

$$P_q\left(S \mid G\right) = P\left(t_{1q}^*\right) \cap P\left(t_{2q}^*\right) \cap \ldots P\left(t_{Kq}^*\right) \tag{3}$$

where $P(t^*_{kq})$ is the probability that individual q selects threshold t^* of criterion k ($k=1,2,\ldots K$). The selection of criteria threshold values represents individual constraints. Hence the selection of threshold t^*_{kq} of criterion k ($k=1,2,\ldots K$) by individual q is related to a vector of individual characteristics Z_{kq}, a vector of coefficients to be estimated α_k, and an error term ε_{kq}. Assuming correlated error terms across different criteria thresholds for each individual, the error term ε_{kq} comprises an i.i.d. standard error term u_{kq} and a jointly multivariate distributed error term ζ_{qk} across criteria, which is also i.i.d. across individuals:

$$t_{kq}^* = \alpha_k^{'} Z_{kq} + \varepsilon_{kq} = \alpha_k^{'} Z_{kq} + \xi_{kq} + u_{kq} \tag{4}$$

The symmetrical correlation matrix Σ_{kq} of the error terms may be written as in equation (4) for K criteria, where the off-diagonal elements capture the correlation among different criteria thresholds:

$$\Sigma_{kq} = \begin{bmatrix} 1 & a_{1,2} & \cdots & a_{1,K-1} & a_{1,K} \\ & 1 & a_{2,3} & \cdots & a_{2,K} \\ & & 1 & \ddots & \vdots \\ & & & \ddots & a_{K-1,K} \\ & & & & 1 \end{bmatrix} \tag{5}$$

The representation of the selection of a combination of correlated thresholds is inspired by the mixed ordered-response model developed by Bhat and Srinivasan (2005). Based on the assumption that the error terms u_{kq} and ξ_{kq} have a normal distribution, a mixed ordered-response probit is utilized. The probability of individual q selecting threshold t^* of the criterion k is:

$$P\left(\theta_{(m-1)_k} < t^*_{kq} \leq \theta_{m_k}\right) = \Phi\left(\theta_{(m-1)_k} - \left(\alpha'_k Z_{kq} + \xi_{kq}\right)\right) - \Phi\left(\theta_{m_k} - \left(\alpha'_k Z_{kq} + \xi_{kq}\right)\right) \tag{6}$$

where $\theta_{(m-1)k}$ and θ_{mk} are the lower and upper bounds of the threshold category m_k ($m_k=1,2,\ldots,M_k$) that represents the threshold t^*_{kq}, and Φ represents the cumulative standard normal distribution. Relatively to each criterion k, the corresponding log-likelihood function for individual q is written as follows:

$$L_q\left(\alpha_k, \theta_k \mid \xi_{kq}\right) = \prod_{m_k=1}^{M_k}\left[\Phi\left(\theta_{(m-1)_k} - \left(\alpha'_k Z_{kq} + \xi_{kq}\right)\right) - \Phi\left(\theta_{m_k} - \left(\alpha'_k Z_{kq} + \xi_{kq}\right)\right)\right]^{d_{m_k q}} \tag{7}$$

where d_{mkq} is an indicator function that is equal to one if individual q selects the threshold category m of criterion k, and zero otherwise. The unconditional likelihood of individual q selecting a combination of K criteria thresholds yielding choice set S_q is expressed as:

$$L_q\left(S_q \mid G\right)=\int_{\xi_{1q}}\dots\int_{\xi_{Kq}}\left(\prod_{m_k=1}^{M_k}\left[\Phi\left(\theta_{(m-1)_1}-\left(\alpha_1^{'}Z_{1q}+\xi_{1q}\right)\right)-\Phi\left(\theta_{m_1}-\left(\alpha_1^{'}Z_{1q}+\xi_{1q}\right)\right)\right]^{d_{m_1q}}\right.$$
$$\left.\dots\prod_{m_k=1}^{M_k}\left[\Phi\left(\theta_{(m-1)_K}-\left(\alpha_K^{'}Z_{Kq}+\xi_{Kq}\right)\right)-\Phi\left(\theta_{m_K}-\left(\alpha_K^{'}Z_{Kq}+\xi_{Kq}\right)\right)\right]^{d_{m_Kq}}\right) \quad (8)$$
$$\dots\varphi_K\left(\xi_{1q},\dots,\xi_{Kq}\right)d\xi_{1q}\dots d\xi_{Kq}$$

where φ_K is a standard K-variate density function.

2.2. Choice stage: accommodating a flexible error structure

A flexible error structure is accommodated at the choice stage by employing a mixed logit model formulation. The mixed logit model formulation can alternatively represent error components that create correlations across the alternatives, and random parameters that represent taste heterogeneity across the population (Train, 2009).

Assuming the existence of similarities across the alternatives within the viable choice sets, the choice stage is represented by the error component logit to account for nested correlation patterns across alternatives. Assuming that Q individuals share the same universal realm G, that the attribute values for any alternative j are identical across individuals and that the nesting structure is the same for all individuals, the likelihood of individual q to choose alternative i out of the viable choice set S_q is as follows:

$$L_q\left(i \mid S\right)=\prod_{i\in S_q}\left[\int\frac{\mathrm{e}^{\left(\beta' X_i+\sum_{r=1}^{R}\mu_r d_{ir}\right)}}{\sum_{j\in S_q}\mathrm{e}^{\left(\beta' X_j+\sum_{r=1}^{R}\mu_r d_{jr}\right)}}f\left(\mu \mid \omega\right)d\mu\right]^{d_{qi}} \quad (9)$$

where X_i and X_j are vectors of attribute values of the alternatives i and j, respectively, μ is a vector of R error components μ_r representing each nest r, d_{ir} and d_{jr} are indicators that are equal to 1 if alternatives i and j belong respectively to nest r, and zero otherwise, and d_{qi} equals unity if individual q chooses alternative I, and zero otherwise. The vector β contains the fixed coefficients to be estimated, and the error components μ_r are i.i.d. normally distributed with zero mean and standard deviation σ_r to be estimated. The variance σ_r captures the magnitude of the correlation and plays an analogous role as the nesting coefficient of the nested logit model (Train, 2009).

Assuming the existence of taste heterogeneity across the population, the choice stage is represented by the random coefficients logit (McFadden and Train, 2000).

In order to capture taste differences across individuals, the random coefficients logit assumes that the coefficients in the utility function have a known continuous distribution across the population. Assuming that Q individuals share the same universal realm G, that the attribute values for any alternative j are identical across individuals, that the representative utility is linear in parameters and that the coefficients vary across individuals, the likelihood of individual q to choose alternative i out of the viable choice set S_q is as follows:

$$L_q\left(i \mid S\right) = \prod_{i \in S_q} \left[\int \frac{\mathrm{e}^{\left(\beta' X_i\right)}}{\sum_{j \in S_q} \mathrm{e}^{\left(\beta' X_j\right)}} f\left(\beta \mid \omega\right) d\beta \right]^{d_{qi}} \tag{10}$$

where X_i and X_j are vectors of attribute values of the alternatives i and j, respectively, and β is a vector of coefficients to be estimated. The vector β is distributed across the population with a continuous density function $f(\beta|\omega)$ that is described by a vector of coefficients ω to be estimated. In the current study, a normal density function is assumed for different parameters, and hence the vector of coefficients ω contains the means and variances of their distributions.

2.3. Estimation of the semi-compensatory model

Choice set formation and choice from considered options are distinct mental processes (Bovy, 2009). Hence, although the choice depends on the retained choice set, the error terms of the non-compensatory choice set formation and the compensatory choice are uncorrelated. Hence, the combined unconditional log-likelihood for a population of Q individuals who choose their most preferred alternative i from their viable choice sets S_q extracted from the universal realm of all the possible alternatives can be written as:

$$LL = \sum_{q=1}^{Q} \ln\left[L_q\left(i \mid S_q\right) L_q\left(S_q \mid G\right) \right] \tag{11}$$

In particular, the unconditional log-likelihood of the MMOP-ECL model, which jointly represents the conjunctive heuristic with a multidimensional mixed ordered-response probit model and the utility-based choice with an error components logit model, is written as follows:

$$\begin{aligned} LL\left(\alpha_k, \theta_k, \beta, \lambda_s\right) = \sum_{q=1}^{Q} \ln \Bigg\{ \prod_{i \in S_q} \left[\int \frac{\mathrm{e}^{\left(\beta' X_i + \sum_{r=1}^{R} \mu_r d_{ir}\right)}}{\sum_{j \in S_q} \mathrm{e}^{\left(\beta' X_j + \sum_{r=1}^{R} \mu_r d_{jr}\right)}} f\left(\mu \mid \omega\right) d\mu \right]^{d_{qi}} \cdot \\ \cdot \int_{\xi_{1q}} \cdots \int_{\xi_{Kq}} \left(\prod_{m_k=1}^{M_k} \left[\Phi\left(\theta_{(m-1)_1} - \left(\alpha_1' Z_{1q} + \xi_{1q}\right)\right) - \Phi\left(\theta_{m_1} - \left(\alpha_1' Z_{1q} + \xi_{1q}\right)\right) \right]^{d_{m_1 q}} \right. \\ \left. \cdots \prod_{m_k=1}^{M_k} \left[\Phi\left(\theta_{(m-1)_K} - \left(\alpha_K' Z_{Kq} + \xi_{Kq}\right)\right) - \Phi\left(\theta_{m_K} - \left(\alpha_K' Z_{Kq} + \xi_{Kq}\right)\right) \right]^{d_{m_K q}} \right) \\ \ldots \varphi_K\left(\xi_{1q}, \ldots, \xi_{Kq}\right) d\xi_{1q} \ldots d\xi_{Kq} \Bigg\} \end{aligned} \tag{12}$$

The unconditional log-likelihood of the MMOP-RCL model, which jointly represents the conjunctive heuristic with a multidimensional mixed ordered-response probit model and the utility-based choice with a random coefficients logit model, is written as follows:

$$\begin{aligned} LL\left(\alpha_k, \theta_k, \beta, \lambda_s\right) = \sum_{q=1}^{Q} \ln \Bigg\{ \prod_{i \in S_q} \left[\int \frac{\mathrm{e}^{\left(\beta' X_i\right)}}{\sum_{j \in S_q} \mathrm{e}^{\left(\beta' X_j\right)}} f\left(\beta \mid \omega\right) d\beta \right]^{d_{qi}} \cdot \\ \cdot \int_{\xi_{1q}} \cdots \int_{\xi_{Kq}} \left(\prod_{m_k=1}^{M_k} \left[\Phi\left(\theta_{(m-1)_1} - \left(\alpha_1' Z_{1q} + \xi_{1q}\right)\right) - \Phi\left(\theta_{m_1} - \left(\alpha_1' Z_{1q} + \xi_{1q}\right)\right) \right]^{d_{m_1 q}} \right. \\ \left. \cdots \prod_{m_k=1}^{M_k} \left[\Phi\left(\theta_{(m-1)_K} - \left(\alpha_K' Z_{Kq} + \xi_{Kq}\right)\right) - \Phi\left(\theta_{m_K} - \left(\alpha_K' Z_{Kq} + \xi_{Kq}\right)\right) \right]^{d_{m_K q}} \right) \\ \ldots \varphi_K\left(\xi_{1q}, \ldots, \xi_{Kq}\right) d\xi_{1q} \ldots d\xi_{Kq} \Bigg\} \end{aligned} \tag{13}$$

In both model variations, d_{mkq} is an indicator function that is equal to one if individual q selects the threshold category m of criterion k, and zero otherwise, and d_{qi} is an indicator function that is equal to one if individual q chooses alternative i, and zero otherwise. α_k, θ_k, β and λ_s are vectors of coefficients to be estimated.

The coefficients of both the conjunctive stage and the utility maximization stage are estimated simultaneously. Although sequential estimation is possible and provides consistent estimates, simultaneous estimation is preferred due to the efficiency of the estimates, since all information is utilized in the estimation of each parameter (Train, 2009). Since the model does not have a closed-form expression, it must be approximated numerically and hence is estimated by maximum simulated likelihood (MSL) with 500 standard Halton draws. The multi-dimensional integrals at the conjunctive stage are simulated in a similar manner to Bhat and Srinivasan (2005) with the true correlation pattern across different criteria thresholds serving as an input for the estimation. For representing random taste variation, further integral dimensions are added for representing the choice stage.

2.4. Elasticity at the choice stage

The calculation of the direct and indirect elasticity at the choice stage can provide insight regarding the impact of policy changes, such as for example an increase in apartment prices for a certain apartment type or in a certain neighborhood.

The calculation of the direct elasticity $e_{i,i}$ at the choice stage, namely the percentage change in the choice probability of alternative i due to a change in the attribute n of alternative i, differentiates between two cases: (i) the change in the attribute influences the choice probability of alternative i within a given choice set, (ii) the change in the attribute influences the inclusion of alternative i within a given choice set S_d.

In the first case, the derivative of the probability function can be calculated since the probability function is continuous within each choice set. Since the two stages are uncorrelated, the choice probability of the choice set S_d is not influenced by the change in the attribute n. Consequently, the elasticity is expressed as follows:

$$e_{i,i}=\frac{\sum_{d=1}^{D}P_q\left(S_d\,|\,G\right)\partial\left[P_q\left(i\,|\,S_d\right)\right]}{\partial x_{qin}}\cdot\frac{x_{qin}}{\sum_{d=1}^{D}P_q\left(S_d\,|\,G\right)P_q\left(i\,|\,S_d\right)} \tag{14}$$

In the second case, in which attribute n serves as elimination criterion and the change is sufficiently large, it influences the inclusion of alternative i within a given choice set. Namely, alternative i is included in different choice sets before and after the change, although the selection probability of the choice sets themselves remain constant as they are only dependent on individual intrinsic constraints. Hence, the choice probability of alternative i before and after the change is no longer continuous and only the arc elasticity can be calculated:

$$\begin{aligned} e_{i,i}&=\frac{\Delta P_q\left(i\,|\,G\right)}{\Delta x_{qin}}\cdot\frac{x_{qin}}{P_q\left(i\,|\,G\right)}=\\ &=\frac{\left(\sum_{d_2=1}^{D_2}P_q\left(S_{d_2}\,|\,G\right)P_q\left(i\,|\,S_{d_2}\right)-\sum_{d_1=1}^{D_1}P_q\left(S_{d_1}\,|\,G\right)P_q\left(i\,|\,S_{d_1}\right)\right)}{\Delta x_{qin}}\cdot\frac{x_{qin}}{\sum_{d_1=1}^{D_1}P_q\left(S_{d_1}\,|\,G\right)P_q\left(i\,|\,S_{d_1}\right)}\end{aligned} \tag{15}$$

where S_{d1} and S_{d2} are the choice sets that contain alternative i before and after the change in the attribute n of alternative i, respectively. D_1 is the number of choice sets S_{d1} and D_2 is the number of choice sets S_{d2} that contain alternative i.

The calculation of the cross elasticity, namely the percentage change in the choice probability of alternative i due to a change in the attribute n of alternative j, differentiates between three cases: (i) the two alternatives do not share the same choice set; (ii) the alternatives share the same choice set before and after the change, (iii) the alternatives share the same choice set either before or after the change.

In the first case, the change in the attribute of alternative *j* does not influence the choice probability of alternative *i*. In the second case, the choice probability function for alternative i is continuous, and hence the cross elasticity of alternative *i* with respect to a change in the attribute *n* of alternative *j* is expressed as follows:

$$e_{i,j} = \frac{\partial P_q(i|G)}{\partial x_{qjn}} \cdot \frac{x_{qjn}}{P_q(i|G)} = \frac{\sum_{d=1}^{D} P_q(S_d|G)\partial\left[P_q(i|S_d)\right]}{\partial x_{qjn}} \cdot \frac{x_{qjn}}{\sum_{d=1}^{D} P_q(S_d|G)P_q(i|S_d)} \tag{16}$$

In the case that the composition of the choice sets that contain alternative *i* is altered as a result of alternative *j* being included, excluded or moved between choice sets, the choice probability of alternative *i* is no longer continuous and the cross elasticity is calculated as follows:

$$e_{i,j} = \frac{\Delta P_q(i|G)}{\Delta x_{qjn}} \cdot \frac{x_{qjn}}{P_q(i|G)} =$$
$$= \frac{\left(\sum_{d=1}^{D} P_q\left(S_{d_{post}}|G\right)P_q\left(i|S_{d_{post}}\right) - \sum_{d=1}^{D} P_q\left(S_{d_{pre}}|G\right)P_q\left(i|S_{d_{pre}}\right)\right)}{\Delta x_{qjn}} \cdot \frac{x_{qjn}}{\sum_{d=1}^{D} P_q\left(S_{d_{pre}}|G\right)P_q\left(i|S_{d_{pre}}\right)} \tag{17}$$

where $S_{d_{pre}}$ are the choice sets that contain alternative *i*, considering the composition before the change and $S_{d_{post}}$ represent the same choice sets as $S_{d_{post}}$, but with the altered composition according to the change induced by alternative *j*.

3. Empirical context and estimation sample

The model is applied to the context of off-campus apartment rental choice of students in a metropolitan core. The following sections discuss the importance of analyzing students' residential choice, describe the estimation sample and provide details regarding the variable specification for model estimation.

3.1. Background

In recent decades, students have become a highly influential player in the local private rented sector (PRS) in university cities, and in some cases the estimated proportion of students in the PRS are 50%-60% (Rugg et al., 2002; Charbonneau et al., 2006). At the neighborhood level the proportion can be higher since students prefer neighborhoods that are either adjacent to campus or offer abundance of social activities (Rugg et al., 2002; Smith and Holt, 2007; Hubbard, 2008).

In addition to their role in the PRS, students have a substantial impact on the local communities. The benefits of student influx are the support of local economy (Hubbard, 2008), the revitalization of the urban core and the development of a creative culture (Charbonneau et al., 2006). The externalities are the formation of seasonal sub-communities that induce physical, economic and social concerns among local inhabitants (Kenyon, 1997; Smith and Holt, 2007; Hubbard 2008) and to the competition between students and other low-income renters (McDowell, 1978).

The provision of attractive student accommodations that encourages a balanced spatial distribution of student influx, a heterogeneous student population and long residence duration may be the key to maintaining the benefits of student influx while mitigating its externalities (Macintyre, 2003; Smith, 2008). Nevertheless, the issue of students' off-campus residential preferences is scarcely explored (Charbonneau et al., 2006). In fact, the only discrete choice models applied to student residential choice are the model of Kaplan et al. (2009, 2011a). However, these models do not accommodate nested substitution patterns or random taste heterogeneity, which are highly important for residential choice. Hence, the capabilities of the current semi-compensatory model make it a unique contribution to modeling students' residential choice.

3.2. Data collection

The data sample for model estimation is retrieved from a web-based experiment replicating rental apartment choice by students.

In the experiment, participants searched a synthetically generated apartment dataset by a list of pre-defined criteria threshold values, and from the resulting choice set they chose their three most preferred apartments for completing a prospective rental transaction.

The apartment dataset, which was constructed on the basis of a statistical analysis of local real-estate databases, consisted of rental apartments characterized by their location, monthly rent price, structural features, neighborhood amenities, electrical appliances, number of roommates and smoking policy. The criteria for searching the dataset were apartment sharing, neighborhood, monthly rent price, number of rooms, walking time to campus, noise level and parking availability.

A questionnaire supplemented the experiment by collecting participants' socio-economic characteristics, as well as attitudes and perceptions about relevant issues to rental apartment choice. Individual characteristics include socio-economic characteristics, transportation related variables, and residential characteristics. Attitudinal and perception items are related to price, studying at home versus on-campus, preference for non-motorized modes and travel minimization.

Further details regarding the theoretical foundation of the data collection method for the simultaneous elicitation of thresholds and choice outcomes, the construction of the apartment dataset, the questionnaire design and the web-based platform are provided by Kaplan et al. (2010, 2011b).

The data sample for model estimation consists of 1,893 observations of choice outcomes and their corresponding thresholds from 631 students studying in the city of Haifa, in the north of Israel, who participated in the experiment.

Table 1 summarizes the population sample characteristics. The sample is representative of the student population on campus in terms of gender distribution (Central Bureau of Statistics, 2006), median age (Central Bureau of Statistics, 2005a), and residential arrangements (Central Bureau of Statistics, 2005b).

[Insert Table 1 about here]

4. Model estimation results

Table 2 presents the estimation results for the two flexible error structure variations of the proposed semi-compensatory model. Specifically, the semi-compensatory model with a nested correlation pattern across alternatives at the choice stage (MMOP-ECL) and the semi-compensatory model with random taste variation across the population at the choice stage (MMOP-RCL) are presented. The two models are compared to the semi-compensatory model proposed by Kaplan et al. (2009), which combines correlated thresholds and an i.i.d. error structure at the choice stage (MMOP-MNL).

Three criteria are represented in the estimated model: apartment sharing, neighborhood and monthly rent price. These criteria were ranked as the most important rental apartment attributes in a preliminary survey among 74 students and were utilized for searching the dataset by the entire population sample.

Apartment sharing and neighborhood are represented by binary probit models. The criterion of apartment sharing differentiates between vacant and shared apartments, and is treated in the current study as an ordered criterion since, given no other information, vacant apartments are naturally better than shared apartments. The neighborhood criterion differentiates between two neighborhood types that are attractive to students. The first type, represented by the Neve-Shanan neighborhood, is located near the campus but offers little employment or leisure opportunities. The second type, represented by the Carmel neighborhood, is located farther away from the campus but offers abundant shopping and leisure opportunities, as well as high accessibility to student jobs located in a nearby high-technology compound. The two neighborhoods are treated as ordered by their perceived location amenities since, according to the results of the questionnaire, the neighborhood of Carmel received on average higher scores than the neighborhood of Neve-Shanan in terms of amenities. The difference between the two neighborhoods in terms of proximity to campus, leisure and work opportunities is illustrated in Figure 2.

[Insert Figure 2 about here]

The price threshold is best described by the ordered-response probit model with 11 categories (200, 250,…,700). These thresholds are driven from the distribution of selected threshold categories as shown by Kaplan et al. (2010). The chosen criteria yield 41 threshold combinations that lead to the formation of non-empty choice sets. Spearman's correlations across the criteria serve as an input for the model estimation. Spearman's correlation between monthly rent price and neighborhood is 0.415, between monthly rent price and apartment sharing is 0.674, and between apartment sharing and neighborhood is 0.313. All the correlations are significant at the 0.01 significance level.

The relevant universal realm for the population sample contains 200 apartments, which are all the available apartments in the generated dataset for the above mentioned neighborhoods. A priori deterministic restrictions on the availability of the alternatives are not imposed for the purpose of model estimation. However, when the respondents were asked to state their three most preferred apartments, they were not allowed to state the same alternative twice. Hence, for each choice, the alternatives with higher priority ranking are excluded from the choice set prior to the model estimation. In the current study, repeated choices of the same individual are treated as panel data.

Socio-economic explanatory variables are directly included in the model, whereas perceptions and attitudes are incorporated after performing factor analysis.

Last, the current model specification does not consider the possibility of "no choice" since investigating market expansion is out-of-scope for the current research.

[Insert Table 2 about here]

The first three parts of table 2 describe the determinants of threshold selection related to apartment sharing, neighborhood and monthly rent price, respectively. The fourth part presents the relative importance of apartment attributes at the utility-based choice stage, given the viable choice set.

4.1. Determinants of apartment sharing

On average, the respondents prefer to reside in shared apartments. The propensity to delimit the dataset to vacant apartments increases according to: (i) the progression of the respondents' lifecycle in terms of age, marital status and monthly expenses, and daily car availability; (ii) current residence in a vacant apartment.

The propensity to delimit the dataset to shared apartments increases with (i) daily trips to campus and the preference to study there, possibly from reasons of easing apartment chores; (ii) the preference of non-motorized modes, possibly from reasons of ride sharing, as 60.9% of the respondents who normally walk or bike share a ride occasionally; (iii) current residence in a shared apartment.

4.2. Determinants of neighborhood selection

On average, the respondents prefer to reside Neve-Shanan. The propensity to delimit the dataset to Neve-Shanan neighborhood, which is adjacent to campus, is related to daily travel frequency to campus and the preference to study there.

The propensity to delimit the dataset to the Carmel neighborhood increases according to: (i) daily car availability as it allows disperse activity patterns and provides easy accessibility to campus; (ii) studying in the Faculty of Medicine as the Carmel neighborhood offers better accessibility to the medical campus; (iii) greater perceived difference in accessibility to student jobs, due to the high accessibility of the neighborhood to Haifa's main high-technology industrial park that offers abundance of job opportunities to students, and the abundance of job possibilities in shops and dining places; (iv) greater availability of green areas in favor of Carmel relatively to Neve-Shanan.

4.3. Determinants of monthly rent price

The propensity to select higher price thresholds increases according to: (i) progression of the student’s lifecycle and socio-economic status; (ii) self-reported price knowledge; (iii) current residence in Haifa’s upper class neighborhoods or the center of Israel; (iv) current residence in an apartment alone or with a spouse. Possibly, students who are currently paying high rent prices have a greater propensity to select higher price thresholds.

The propensity to select higher price thresholds decreases according to: (i) habit to travel daily to campus, likely related to shorter time spent in the apartment with respect to the campus; (ii) greater apartment search experience, likely reflecting a greater propensity to undergo the burden of replacing a status quo alternative with a more cost-efficient one.

4.4. Apartment attributes

For each respondent, apartment sharing and neighborhood are determined at the choice set formation stage and do not vary within the viable choice set. Monthly rent price and the number of roommates vary within the viable choice set and hence serve as explanatory variables at the utility maximization stage.

The propensity of renting an apartment increases according to the increase of: (i) quality of structural features (i.e., size and renovation status); (ii) availability of security bars; (iii) availability of a solar water heater; (iv) availability of air conditioning; (v) parking availability; (vi) location amenities (i.e., view and noise level).

The propensity of renting an apartment decreases according to the increase in terms of: (i) apartment monthly rent; (ii) floor number, possibly due to the scarcity of elevators in the two neighborhoods; (iii) number of roommates; (iv) walking distance from campus; (v) roommates' pro-smoking policy, possibly since 87.0% of the respondents are non-smokers.

4.5. Effect of incorporating a flexible error structure

The MMOP-ECL model is estimated with a mixed nested structure differentiating between ground floor apartments and other apartments. When compared to the MMOP-MNL by likelihood ratio (LR) test, the LR test value rejects at the 0.05 significance level the null hypothesis of independent correlation patterns across alternatives within the viable choice sets (LR=33.81>5.99), as similarity patterns exist across non ground floor apartments.

The MMOP-RCL model investigates random taste variation with respect to security bars, a stunning view and apartment renovation. When compared to the MMOP-MNL by LR test, the test value rejects the null hypothesis of homogeneous responsiveness across the population with respect to attributes of apartments within the viable choice sets (LR = 31.57 > 7.81). The model estimation results indicate that while there is no random taste variation with respect to the availability of security bars, large taste variations exist with respect to the availability of view and apartment renovation.

In addition to the LR test, the proposed semi-compensatory model variations with a flexible error structure at the choice stage are compared to their predecessor, namely the MMOP-MNL, in terms of their in-sample predictive ability. The predictive ability is typically assessed by the percent correctly predicted (PCP), namely the percent of observations in which the actual choice outcomes corresponds to the alternative with the highest probability. This approach is criticized for its inability to incorporate uncertainty and to account for the magnitude of the relative difference in the choice probabilities (Train, 2009). Hence, in addition to the traditional approach, the PCP is assessed in the current paper as the percent of observations in which the actual choice outcomes corresponds to one of the three most probable alternatives. This adjustment allows incorporating uncertainty and considering alternatives with very similar choice probabilities. Considering the traditional approach, the PCP of the MMOP-MNL is 9.1%, while the PCP of the MMOP-ECL and the MMOP-RCL are 11.5% and 11.4%, respectively, namely an increase of roughly 26% in the predictive ability of the model variations with the flexible error structure. The adjusted PCP for three alternatives is 23.7% for the MMOP-MNL, versus 26.6% and 26.5% for the MMOP-ECL and the MMOP-RCL, respectively, an increase of roughly 12% in the predictive ability of the model variations with the flexible error structure.

5. Discussion, limitations and further research

In decisions involving many alternatives, such as residential, workplace and route choice, individuals conduct a two-stage decision process of eliminating non-viable alternatives and choice from the remaining choice set. Semi-compensatory discrete choice models, show promise in mathematically representing such decisions. However, despite achieved scientific progress in semi-compensatory model development, still a major barrier for their implementation is their underlying assumption of i.i.d. error terms across alternatives in the representation of the utility-based choice.

The current study extends the previous work of Kaplan et al. (2009,2010, 2011a), and Kaplan and Prato (2010), who managed to alleviate the simplifying assumptions embedded in semi-compensatory models based on Manski’s (1977) formula with respect to the number of alternatives and choice sets, and the representation of threshold selection. The current study relaxes the assumption of the i.i.d. error structure at the choice stage, thus removing an important barrier for model implementation. Specifically, the current study shows the ease of embedding correlation patterns across alternatives and alternatively random taste heterogeneity in its predecessor.

The model is applied to students' off-campus apartment rental choice and provides a valuable insight regarding its underlying determinants. The choice set formation is governed by price, apartment sharing and neighborhood, and depends on socio-economic characteristics, travel preferences, price perceptions and study-place preferences. Following choice set formation, students consider apartment price, structural features, number of roommates and their smoking attitudes, electrical appliances that influence recurrent costs and neighborhood amenities. The results also indicate that students differentiate between ground floor and other apartments and large taste variation exists across students with respect to the preferences of renovated apartments and apartments with a view.

The LR test results and the prediction results show the importance of considering a flexible error structure into semi-compensatory models, since the addition of alternatively a nested substitution pattern and random taste variation improve the goodness-of-fit and the prediction ability of the model compared to a semi-compensatory model with an i.i.d. error structure at the choice stage.

The traits of the proposed semi-compensatory model, namely applicability to decisions entailing many alternatives, refined threshold representation, and flexible error structure in the utility-based choice stage, make it a powerful work-horse for widespread applications in consumer research, transport and urban planning. Moreover, the model can be readily incorporated in activity-based models and joint transport and land-use models.

The current model has several limitations that indicate exciting and challenging future research directions towards the realization of the full potential of semi-compensatory models.

Firstly, the current study assumes the same model structure for the entire population, while recent studies suggest that the model structure may vary across population segments. Zhu and Timmermans (2010) found that criteria selection is context dependent. Possibly, criteria selection may also vary across population segments. According to Ishaq et al. (2010), variation across the population exists with respect to the utility-based model structure (e.g., existence of nests, number of nests and decision sequence). Hence, an interesting future research direction is the consideration of latent class models and population segmentation in semi-compensatory choice.

Secondly, the current study postulates utility maximization at the choice stage, while studies indicate the existence of other decision rules such as attribute dominance (Olshavsky, 1979) and regret minimization (Chorus et al., 2008). Consequently, a natural future research direction is the consideration of alternative decision rules at the choice stage of in semi-compensatory choice.

Third, the current study hypothesizes discrete decision at the choice stage, while studies have shown that utility-based decisions also involve discrete-continuous choices such as activity and time use (Bhat et al., 2006; Pinjari and Bhat, 2010) and residential location, activity and time use (Pinjari et al., 2009). A good example for such a discrete-continuous decision with single discreteness is students' residential choice, in which students eliminate alternatives according to apartment sharing and price, and then jointly decide upon a dwelling unit and rental period duration. An example of a multiple-discrete-continuous decision is the purchase of real-estate assets by companies for investment purposes. Upon the elimination of real-estate assets by criteria (e.g., location, building type), companies may choose to allocate their expenditure simultaneously to several assets that satisfy their criteria. As such choices may involve different substitution patterns across alternatives. Hence an important future research direction would be to incorporate multiple-discrete-continuous models such as the MDCNEV (Pinjari and Bhat, 2010) and other GEV-based discrete-continuous models (Pinjari, 2011) into the semi-compensatory model framework at the choice stage.

Fourthly, while the current study takes a stationary approach, a new stream of dynamic models that accommodate non-stationary market supply, historical trends, and time dimension in the choice set formation have been hypothesized as potentially useful in the context of residential choice and are currently under development (e.g., Benenson, 2004;

Chen et al., 2009; Devisch et al., 2009; Habib and Miller, 2009). Hence, it would be interesting to consider these aspects in future semi-compensatory models.

Last, the current study assumes that the error terms of the choice set formation stage and the utility maximization stage are uncorrelated. Although this assumption is explicitly supported by the literature (Manski, 1977; Gensch, 1987; Bovy, 2009), the two cognitive processes are employed by the same individual. Moreover, in the current study apartment price has a significant influence both as a constraint on the choice set formation and as an attribute once the choice set is formed. This result is in line with the findings of Chakravarti et al. (2006) that individuals may use the same attributes both at the elimination stage and at the choice process from the considered choice set. A potential future direction inspired by the works of Pinjari et al. (2009) and Bhat et al. (2009) may emerge from including log-sum variables from the choice stage at the choice set formation stage in a similar manner.

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List of figures and tables

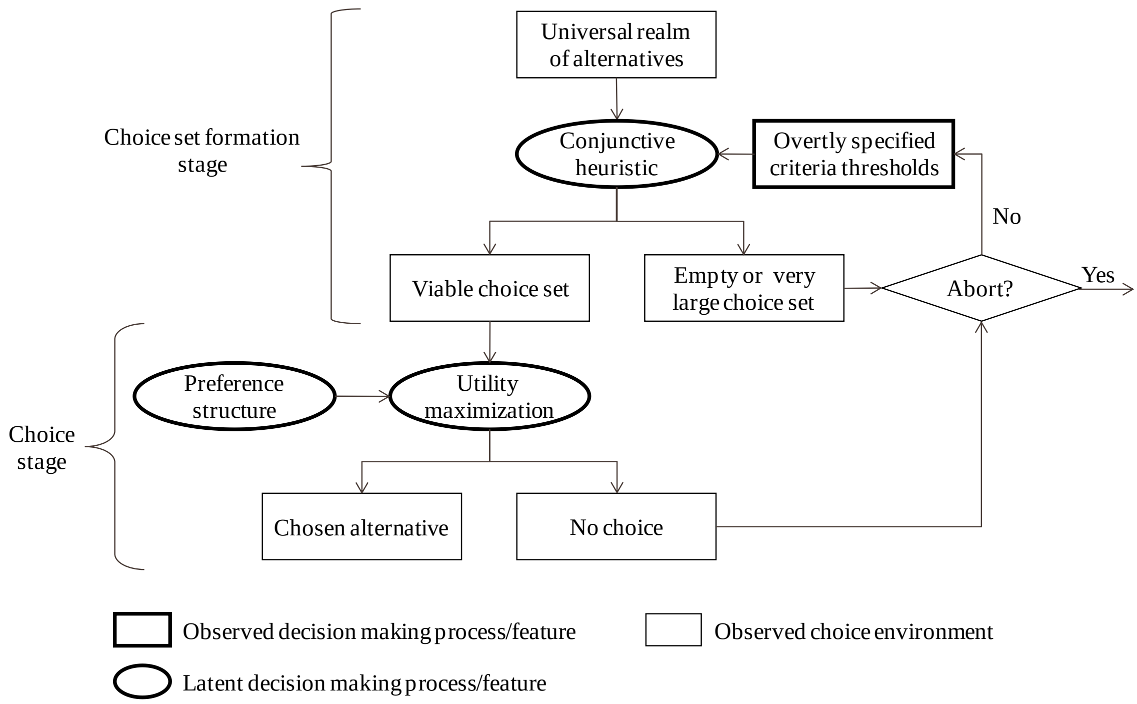

Figure 1. Two-stage decision process

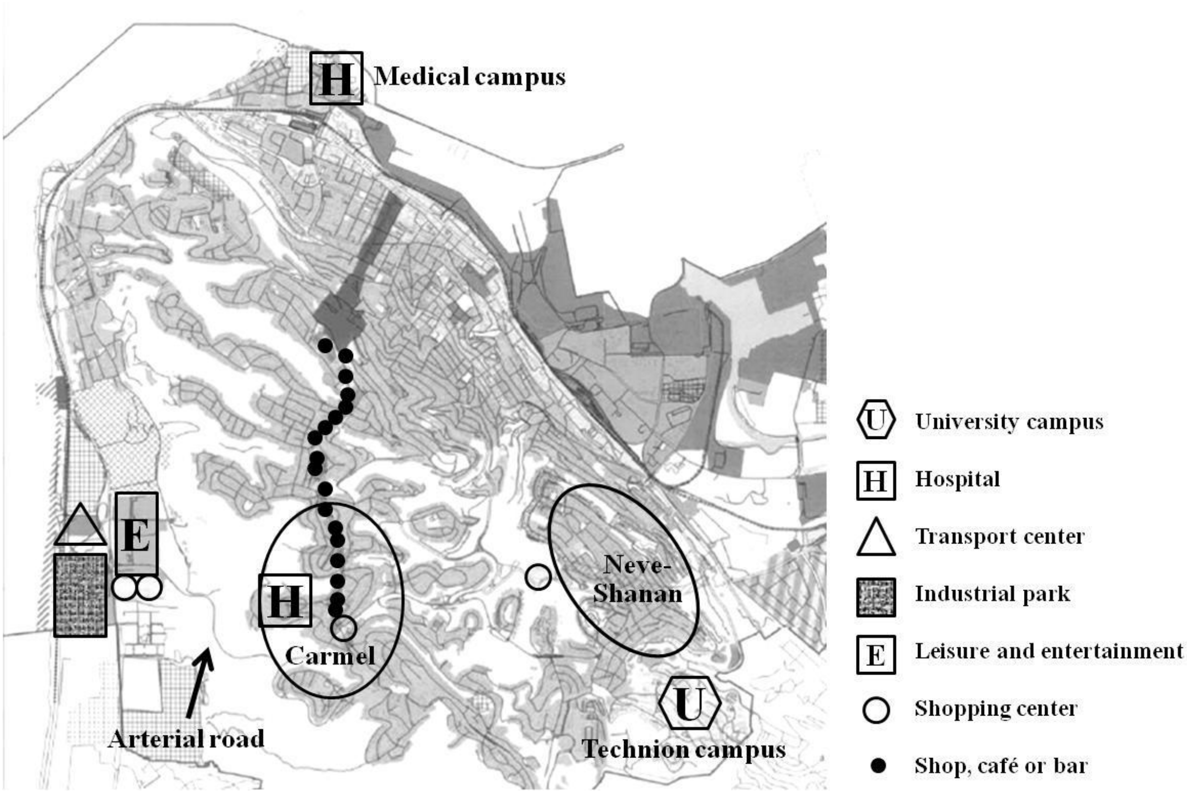

Figure 2. The neighborhoods of Carmel and Neve-Shanan

Table 1

Sample characteristics

Variable	Categories (%)				
Gender	Male	Female			
	60.7	39.3			
Marital status	Married	Single			
	29.8	70.2			
Age	≤ 21	22-24	25-29	30-34	35-44
	7.4	21.4	49.3	18.2	3.6
Income source	Scholarship	Full-time	Part-time	None	
	44.8	12.2	23.9	19.0	
Monthly expenses	≤ $500	$500-$1000	$1000-$1500	≥$1500	No response
	39.1	28.8	15.4	12.8	3.8
Residential arrangement	Dormitories	Rent alone	Rent with roommates	Co-habit with spouse	Parents' house
	33.4	5.9	12.7	36.8	11.3
Residential location	Haifa metropolitan area	Haifa metropolitan outskirts	Tel Aviv	Other	
	75.1	13.8	7.9	3.2	
Car availability	Everyday	2-3 times	Once a week	2-3 times a month	rarely
	42.5	11.6	11.6	7.1	27.3
Smoking	Non-smoker	Occasional smoker	Smoker		
	87.0	7.0	6.0		

Table 2

Semi-compensatory model estimation results

Variable	Description	MMOP-MNL		MMOP-ECL		MMOP-RCL	
		est.	t-stat.	est.	t-stat.	est.	t-stat.
Apartment sharing threshold coefficients							
Constant for a vacant apartment		-0.955	-1.64	-0.929	-1.62	-0.924	-1.61
Marital status	Single [a]	-	-	-	-	-	-
	Married	1.751	7.74	1.754	7.75	1.754	7.74
Gender	Female [a]	-	-	-	-	-	-
	Male	-0.754	-5.64	-0.758	-5.65	-0.757	-5.64
Age	Years	0.058	2.80	0.057	2.83	0.057	2.82
Car availability	Monthly/weekly [a]	-	-	-	-	-	-
	Daily	0.521	3.74	0.519	3.71	0.520	3.71
Trip frequency to campus	Monthly/weekly [a]	-	-	-	-	-	-
	Daily	-0.558	-4.07	-0.558	-4.04	-0.557	-4.03
On-campus studying to benefit from teacher-student communication factor		-0.134	-3.14	-0.133	-3.13	-0.133	-3.12
Monthly expenses	< $750 [a]	-	-	-	-	-	-
	$ 750 - 1000	0.708	3.49	0.688	3.36	0.686	3.35
	$1000 - 1750	0.846	4.58	0.844	4.59	0.844	4.60
Current residential arrangement	Dormitories [a]	-	-	-	-	-	-
	Parents	-	-	-	-	-	-
	Roommates	-0.911	-5.07	-0.915	-5.09	-0.916	-5.10
	Alone	1.036	4.24	1.023	4.19	1.020	4.17
	Spouse	1.310	7.91	1.299	7.85	1.297	7.83
Current residential location	Haifa city [a]	-	-	-	-	-	-
	Haifa suburbs	-0.842	-2.96	-0.911	-3.27	-0.912	-3.27
	Haifa outskirts	-1.285	-6.72	-1.249	-6.42	-1.247	-6.41
	Center of Israel	-	-	-	-	-	-
Location threshold coefficients							
Constant for Carmel neighborhood		-3.955	-5.33	-4.014	-5.37	-4.013	-5.37
Price-quality ratio consciousness factor		-0.240	-4.23	-0.234	-4.14	-0.234	-4.14
Age	Years	0.153	6.60	0.155	6.63	0.155	6.62
Car availability	Monthly/weekly [a]	-	-	-	-	-	-
	Daily	0.736	5.64	0.726	5.59	0.727	5.59
Faculty location	Main campus [a]	-	-	-	-	-	-
	Medical campus	0.790	3.54	0.757	3.36	0.758	3.36
Monthly expenses	< $ 750 [a]	-	-	-	-	-	-
	$ 750 - 1500	0.500	3.17	0.483	3.09	0.483	3.08
	> $1500	0.590	3.18	0.562	3.05	0.561	3.05
Income source	None/scholarship [a]	-	-	-	-	-	-
	Part-time job	-0.334	-1.93	-0.332	-1.93	-0.333	-1.94
	Full-time job	-	-	-	-	-	-
Difference in job opportunities		0.126	3.60	0.125	3.63	0.125	3.63
Difference in green space availability		0.296	7.12	0.297	7.17	0.297	7.15
Preference to study on campus in order to increase study efficiency factor		-0.150	-4.38	-0.152	4.44	-0.152	-4.44

Trip frequency to campus	Monthly/weekly [a]	-	-	-	-	-	-
	Daily	-0.278	-2.14	-0.267	-2.07	-0.267	-2.07
	Price threshold coefficients						
Marital status	Single [a]	-	-	-	-	-	-
	Married	0.924	7.22	0.922	7.27	0.921	7.25
Gender	Female [a]	-	-	-	-	-	-
	Male	-0.390	-4.82	-0.392	-4.86	-0.392	-4.86
Age	Years	0.063	4.63	0.065	4.79	0.064	4.77
Monthly expenses	< $ 500 [a]	-	-	-	-	-	-
	$ 500-750	0.358	3.46	0.348	3.35	0.348	3.35
	$ 750-1500	0.824	6.76	0.806	6.54	0.805	6.53
	> $1500	1.041	6.49	1.012	6.26	1.012	6.26
Income source	None/scholarship [a]	-	-	-	-	-	-
	Part-time job	0.162	1.92	0.169	2.02	0.168	2.01
	Full-time job	-	-	-	-	-	-
Car availability	Monthly/weekly [a]	-	-	-	-	-	-
	Daily	0.341	3.64	0.334	3.54	0.334	3.54
Price-knowledge factor		0.162	6.12	0.160	6.03	0.160	6.03
Apartment search experience	#3 apartment changes [a]	-	-	-	-	-	-
	> 4 apartment changes	-0.554	-3.26	-0.551	-3.23	-0.551	-3.23
Trip frequency to campus	Monthly/weekly [a]	-	-	-	-	-	-
	Daily	-0.504	-5.47	-0.503	-5.44	-0.503	-5.44
Current residential arrangement	Dormitories [a]	-	-	-	-	-	-
	Roommates	-0.330	-2.71	-0.345	-2.85	-0.343	-2.83
	Alone/parents	0.251	2.06	0.236	1.94	0.238	1.95
	Spouse	0.840	6.58	0.820	6.39	0.820	6.39
Current residential location	Haifa – low/medium class neighborhoods [a]	-	-	-	-	-	-
	Haifa – upper class neighborhoods	0.215	1.77	0.222	1.83	0.220	1.82
	Haifa Suburbs	-	-	-	-	-	-
	Haifa outskirts	-	-	-	-	-	-
	Center of Israel	0.771	6.67	0.780	6.73	0.779	6.73
Non-motorized modes preference factor		-0.038	-1.65	-0.036	-1.59	-0.036	-1.59
Travel minimization preference factor		-0.081	-3.04	-0.081	-3.05	-0.081	-3.03
Cut-off points	200 [a]	-	-	-	-	-	-
	250	0.024	0.06	0.058	0.14	0.056	0.13
	300	0.648	1.53	0.679	1.61	0.678	1.61
	350	1.053	2.49	1.082	2.56	1.080	2.55
	400	1.239	3.23	1.397	3.29	1.395	3.29
	450	2.010	4.71	2.034	4.77	2.032	4.76
	500	2.672	6.26	2.692	6.30	2.689	6.29
	550	3.558	8.32	3.571	8.34	3.566	8.33
	600	3.902	9.09	3.912	9.11	3.908	9.09
	650	4.434	10.35	4.420	10.35	4.435	10.33
	700	4.648	10.83	4.653	10.83	4.648	10.81

	Choice stage coefficients given the selected choice set					
Rent price (monthly)	-0.001	-2.44	-0.001	-2.38	-0.002	-2.95
Number of rooms	0.577	11.85	0.597	12.00	0.628	12.02
Number of roommates	-0.353	-4.22	-0.391	-4.63	-0.321	-3.37
Walking time to campus	-0.083	-16.05	-0.084	-15.90	-0.090	-16.09
Quiet apartment	1.476	25.21	1.489	25.31	1.510	24.33
Parking	0.284	4.24	0.296	4.40	0.335	4. 74
Smoking allowed	-0.346	-4.69	-0.390	-5.01	-0.368	-4.75
Security bars (mean)	0.173	3.41	0.172	3.36	0.197	3.36
Security bars (standard deviation)	-	-	-	-	0.277	0.44
Stunning view (mean)	0.365	6.48	0.344	5.97	-1.513	-1.77
Stunning view (standard deviation)	-	-	-	-	4.786	3.02
Renovated (mean)	0.544	9.14	0.552	9.20	0.329	2.55
Renovated (standard deviation)	-	-	-	-	2.270	4.84
Air conditioner	0.318	5.48	0.319	5.47	0.351	5.74
Solar water heater	0.474	5.83	0.475	5.82	0.484	5.71
σ_1 Non ground floor apartment	-	-	0.796	3.05	-	-
σ_2 Ground floor apartment	-	-	0.266	1.74	-	-
Number of observations		1893		1893		1893
Number of parameters		69		71		72
Log-likelihood at zero		-20431.414		-20431.414		-20431.414
Log-likelihood at estimates		-10693.784		-10676.880		-10677.997
McFadden’s adjusted R^2		0.473		0.474		0.474

Note: [a] base category, est. – estimated coefficient, t-stat. – t-statistic.