## ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

## MODELLING DEPARTURE TIME, DESTINATION AND TRAVEL MODE CHOICES BY USING THE GENERALIZED NESTED LOGIT MODEL: AN EXAMPLE FOR DISCRETIONARY TRIPS

Ph.D. THESIS

Mahmoud Morssy Mohamed ELMORSSY

**Department of Civil Engineering** 

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# ISTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

## ZORUNLU OLMAYAN YOLCULUKLAR İÇİN YOLCULUĞA BAŞLANGIÇ ZAMANI YOLCULUĞUN SON NOKTASI VE TÜR SEÇIMLERİNİN GENELLEŞTİRİLMİŞ HİYERARŞİK LOJİT MODEL KULLANILARAK MODELLENMESİ

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### FOREWORD

This dissertation introduces some methodological frameworks that contribute with the notion of connecting different travel dimensions in travel demand modelling literature. By words, I aimed to develop a novel model that jointly links three significant travel dimensions; departure time, destination and travel mode.

Since there is a gap in literature regarding introducing the latent heterogeneity among these three travel dimensions, I have motivated to fill this gap by adopting some sophisticated discrete choice approaches.

I have employed my experiences in the field of transportation modelling (e.g. travel demand modelling, transportation system analysis, estimation and statistics, travel demand surveys, etc.) that I gained during my graduate studies to attain best achievements in both theoretical and practical aspects of this dissertation.

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I'd like to thank my family, my mother Somaya, my wife Nashwa, my children, Malak, Abdulrahman and Maryam, my sister Maysa and my brother Mohamed. I dedicate this work to my father's soul. May the God have mercy on him and placed him into his havens.

March 2020

Mahmoud ELMORSSY



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# ABBREVIATIONS

VOT	: Value of Time
MNL	: Multinomial Logit model
NL	: Nested Logit model
IIA	: Irrelevant of Independent Alternatives
IID	: Identical Independent Distribution
OGEV	: Ordered Generalized Extreme Value model
GNL	: Generalized Extreme Value model
U	: Total random latent utility function
V	: Deterministic component of the latent utility
ASC	: Alternative specific constant
TT	: Total travel time
тс	: Total travel cost
COW	: Car ownership
INC	: Household monthly income
SS	: Student status (1 if student 0 otherwise)
AGE	: Age of the traveller
ATD	: Average travel distance
Q	: Vector of alternative's attributes
С	: Vector of decision maker's characteristics
Т	: Choice set of departure time alternatives
D	: Choice set of destination alternatives
Μ	: Choice set of travel mode alternatives
<b>P</b> [·]	: Probability of choosing a specific alternative
Pr[·]	: Probability of achieving specific conditions
tdm or t,d,m	: Joint choice of a departure time "t", destination "d" and travel mode "m"
uen or u,e,n	: Joint choice of a departure time "u", destination "e" and travel mode "n"

xyz or x,y,z	: Joint choice of travel dimensions "x", "y" and "z"
y x	: Choosing travel dimension "y" given another travel dimension "x"
z y,x	: Choosing travel dimension "z" given travel dimensions "y" and "x"
i or n	: A decision maker
р	: Peak
0	: Off-Peak
e	: Evening
S	: Espark
l	: Local Bazaar
Z	: Ozdilek
c	: Car
b	: Bus
tr	: Tramway

# SYMBOLS

α	: Allocation parameter of OGEV or GNL model
η	: Allocation Parameter of an Extreme Value Distribution
β	: Vector of variable's coefficients
3	: Error term or random component unknown to the analyst
3	: Error term associated with a specific nesting level
θ	: Scale parameter of an Extreme Value Distribution



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#### MODELLING DEPARTURE TIME, DESTINATION AND TRAVEL MODE CHOICES BY USING THE GENERALIZED NESTED LOGIT MODEL: AN EXAMPLE FOR DISCRETIONARY TRIPS

#### SUMMARY

Nowadays, understanding the influences of different temporal and spatial factors on individuals' travel choices becomes essential especially after the pandemic of COVID-19 that invaded the world in 2020. Such an outbreak had its own influences on the future transportation planning studies. By words, policy makers have directed their interests toward newly emergency transportation policies that aim to distribute travels over wider time and space spans in accordance with precautionary and preventive measures to counteract Corona virus or any other similar future virus attacks. However, transportation planning studies still rely on traditional demand modelling approaches such as the four-step model. The four-step model is still exposed to considerable criticism for its shortages in representing the potential correlations between temporal, spatial factors and different travel dimensions which leads to inaccurate representations of individuals' actual travel behaviour. In order to overcome that, some researches have directed their interests toward using choice modelling approach as an alternative to some stages in four-step model. Even though these approaches show better performance in terms of goodness of fit and predictability power, most of them have represented travel dimensions individually rather than jointly. As there is a gap in literature about representing a unified choice model that connect different travel demand dimensions and consider various potential intercorrelation among them, this dissertation contributes filling this gap through introducing three research papers that employ various types of discrete choice models for jointly representing three major travel dimensions; destination, departure time and travel mode. Such models contribute more to mathematical modelling literature of transportation demand models that provide more detailed and specific micro-policy analyses where traditional four-step model cannot.

The presented papers introduce three discrete choice models that differ in the level of accounting for correlation of error terms within elementary alternatives and therefore differ in cross-elasticity pattern while offering computational simplicity. In the first paper, limited number of correlation patterns is introduced by adopting the three-level Nested Logit (NL) models. In the second paper, opposite to traditional NL models that was introduced in previous paper, this paper assesses the effect of considering spatial correlation of adjacent discretionary destinations on the choice of the two other travel dimensions by using the Ordered Generalized Extreme Value (OGEV) approach. The third paper, introduces a novel modelling methodology for using the Generalized Nested Logit (GNL) model to represent multi-dimensional potential correlations; between different travel dimensions (inter-correlation), inside the same travel dimension (inner-correlation) and correlation due to ordered nature travel dimensions (e.g. spatial correlation among destinations and temporal correlation between departure times). Overall, in the published papers, different levels of correlation between departure time, destination and travel mode choices and within each travel

dimension are represented through different assumed correlation structures according to the nesting structure limitations provided by each model. Moreover, the associated formulas for each proposed model that reflect different patterns of correlation (crosselasticity) are explicitly introduced.

From a policy implications standpoint, a calibrated version of departure time, destination and travel mode model will provide policy makers very detailed analyses about the inter-relationships associated with the three travel dimensions (while traditional four-step model cannot provide at micro-level). That leads to more certain, specific, efficient and precise policy decisions. Thus, developing these models can be considered as a significant milestone toward obtaining a consistent, efficient and integrated full-scale model that can lie in all travel demand dimensions (e.g. number and duration of activities for activity and tour-based models).

The developed models have been estimated and calibrated by using shopping and entertainment trips data of Eskisehir city, Turkey. The data have been collected through a household survey that was conducted in 2015 in the context of Eskisehir strategic master plan project which was operated by Eskisehir Metropolitan Municipality. Eskisehir is a city in north-western Turkey. It is considered as a medium sized city with a population of 799724 (2013 census) distributed over about 2678 km<sup>2</sup> area. The collected data include variables that represent attributes of alternatives and individuals' characteristics to be used in models' utility functions. The first group of alternatives' attributes is travel time related attributes where, in vehicle time and out of vehicle time (egress time, at stop waiting time and access time) for each individual trip have been obtained. Moreover, related to travel cost, the fare of public transportation modes (for public transportation users), trip cost for private cars as well as parking fees (for private car users) have been observed for each individual trip.

Within the collected revealed data, a good portion of socio-economic individual characteristics related observations are presented. These data include car ownership, individual's age, monthly income and student status (if respondent is a student or not). The total number of observations related to the determined alternatives has been found to be 529.

The estimation results of each model have been explicitly interpreted in each paper and logical as well as statistical comparisons between pairs of models have been conducted in order to ensure the superiority of more advanced approaches (OGEV and GNL) over the lesser ones (NL). In the light of the estimation results, generally, individuals have been found to jointly decide on "at which departure time", "to which destination" and "by which mode" rather than doing this separately as assumed by traditional four-step model. Neglecting the potential correlation among alternatives of the three travel dimensions has led to inaccurate estimates of measurements' indicators such as Value of Time (VOT) which results finally in incorrect and improper policy decisions.

From another hand gradual improvements in predictability have been observed as the level of the represented correlation increases. That is, three-level NL model was found to offer improvements over Multinomial Logit (MNL) model, OGEV model is prominent over NL model and GNL is superior over all models.

It is possible to argue that the proposed GNL approach has distinct improvements over all other proposed approaches. Its simplicity along with the incomparable flexibility in representing a lot of correlation patterns within and among three vital travel dimensions all of that under a unified modest model qualify it to be prominent. The proposed GNL model has provided very detailed analyses about the interdependencies associated with various departure times, travel modes and discretionary destinations where other models cannot. The estimation results have expressed the powerful analytical ability of the proposed GNL approach where it has the power of capturing unusual correlation patterns. These patterns are thoroughly specific, unexpected, and very difficult to be observed in the market. By words, the dissertation argues that there is no other approach as simple as the proposed GNL and leads to such temporal and spatial specific analyses.

The advantages associated with the proposed GNL approach qualify it to be a strong peer to the traditional four-step model in micro-disaggregate modelling scopes if applied for medium and small-scale planning studies that involve limited number of alternatives in each travel dimension. It may be used with a large number of alternatives in each travel dimensions as well, however, through stratifying the whole population to small segments based on one or more travel dimensions to produce small segments suitable for readily estimation process.

Finally, the proposed GNL methodology represents a time of day-based trip-end distribution model that can reproduce a considerably more accurate transportation mode based origin-destination matrix dependent on time of day. Moreover, unlike traditional four-step models, parameter estimates produced from the GNL model can provide significant indications which precisely reflect the individuals' actual behaviour. Obviously, that can enormously help policy makers to reach a solid perception about the effects of applying various strategies to manage demands through different times of day and towards different destinations.



## ZORUNLU OLMAYAN YOLCULUKLAR İÇİN YOLCULUĞA BAŞLANGIÇ ZAMANI YOLCULUĞUN SON NOKTASI VE TÜR SEÇİMLERİNİN GENELLEŞTİRİLMİŞ HİYERARŞİK LOJİT MODEL KULLANILARAK MODELLENMESİ

### ÖZET

Özellikle 2020 yılı başlarından itibaren ortaya çıkan KOVİD-19 (koronavirüs) küresel salgını sonrasında, bireylerin yolculuklarla ilgili seçimleri üzerinde farklı zamansal ve mekânsal faktörlerin etkilerini anlamak önem kazanmıştır. Bu salgının gelecekteki ulaşım planlama çalışmaları üzerinde önemli etkileri olacağı açıktır. Bu etkilerin arasında, ulaşım sisteminin mevcut salgın ve gelecekte yaşanması muhtemel başka salgınlarda, gerekli önleyici tedbirlere uygun olarak daha geniş zaman ve mekân aralıklarında hizmet vermesini sağlayacak düzenlemeler yapılması da yer almaktadır. Ancak, bu planlamanın hangi yöntemle yapılacağı henüz belirsizdir ve halen yalnızca geleneksel dört aşamalı model kullanılmaktadır. Dört aşamalı model ise bireylerin zaman, mekân ve tür tercihlerini, ortak olarak değerlendirebilmek ve buna bağlı olarak politikalar ortaya koyabilmek açısından yetersiz bir modeldir.

Bu çalışmada; kent içi ulaşım talebinin analizinde, yolculuğa başlangıç zamanı, yolculuğun son noktası ve tür seçimlerinin aralarındaki ilişkileri dikkate alan ve bu seçimlerin beraber olarak değerlendirilebilmesine olanak tanıyan bir model geliştirilmiştir. Bu amaçla üç farklı ayrık seçim modeli tahmin edilmiş ve bu modeller sınanmıştır. Önerilen modeller ve bunların yöntemleri, üç yayın ile açıklanmıştır. Bu üç yayında, söz konusu üç seçim, basitten karmaşığa doğru olacak şekilde, Çok Terimli Lojit (Multinomial Logit, ÇTL) Hiyerarşik Lojit (Nested Logit, HL), Genelleştirilmiş Sıralı Uç Değer (Ordered Generalized Extreme Value, GSUD) ve Genelleştirilmiş Hiyerarşik Lojit (Generalized Nested Logit, GHL) modelleri kullanılarak incelenmiş ve değerlendirilmiştir.

Bu tez çalışmasının amacı, bireylerin zorunlu olmayan yolculuklarında yaptıkları başlangıç zamanı, son nokta ve tür seçimleri arasındaki ilişkilerin tek bir model yapısı ile incelenmesi ve değerlendirilmesidir. Bu üç seçim birbirleriyle ilişkili olmalarına ve birbirlerinden etkilenmelerine rağmen, literatürde üçü arasındaki ilişkileri yeterli düzeyde açıklayan modeller sınırlı sayıdadır ve pratik kullanım alanı bulamamaktadır. Literatürde, bu üç seçim için genellikle ÇTL modeli kullanılmakta ancak bu yaklaşımda, seçimler ayrı ayrı, ikili veya üçlü gruplar halinde incelenebilmektedir. Örneğin; üçlü gruplama yapılan bir ÇTL modelinde her bir seçenek, zaman, son nokta ve tür için üç ayrı seçeneğin bir araya getirilmesi ile oluşturulmaktadır. Ancak, bu tip bir gruplamada birkaç temel eksiklik bulunmaktadır:

(1) Üç farklı seçimin tek bir seçenek haline getirilmesi gerçekçi bir gruplama yaklaşımı değildir. Seçeneklerin birbirleriyle çeşitli düzeyde ilişkileri bulunmakla birlikte, bireyler seçimlerini bu ilişkiden etkilenerek ayrık (bağımsız) olarak yapmaktadır. Bahsedilen yöntemle yapılan bir gruplama, zaman/son nokta/tür seçenek paketleri oluştururken, bireylerin bunları böyle paketler şeklinde değerlendirmesi gerçekte söz konusu değildir.

(2) Özellikle seçenek sayısının fazla olduğu durumlarda, bahsedilen üçlü gruplama modellenemeyecek kadar çok sayıda seçeneğin ortaya çıkmasına neden olabilmektedir. Örneğin; İstanbul'daki alışveriş yolculukları için yapılacak bir çalışmada, yalnızca kentteki alışveriş merkezlerinin sayısı bile modelin oluşturulmasını olanaksızlaştıracaktır. Buna, olası bütün ulaşım türleri ile çok sayıda farklı yolculuk başlangıç zamanlarının eklenmesi çalışmanın karmaşıklık düzeyin fazlasıyla büyütecektir.

(3) Hesaplamada kullanılan ÇTL modeli, her bir seçeneğin hata terimlerinin varyanslarının dağılımının bağımsız ve aynı olduğunu kabul etmektedir. Bunun pratik anlamı, her bir seçeneğin seçimine etkisi olan ancak ölçülemeyen faktörlerin aynı olmasıdır. Bu benzerliğin, zaman, son nokta veya tür seçeneklerinin birbiri arasında var olabileceği kabul edilse bile, bahsedilen seçenek paketleri için böyle bir benzerlikten söz etmek mümkün değildir. Bu tip bir yaklaşımla üretilen modeller tahmin hataları içermektedir (Wen ve Koppelman 2001; Pinjari and Bhat 2010).

ÇTL'nin aksine, üç seçimin bir arada incelenmesine olanak tanıyan HL modelleme yaklaşımı ise, hiyerarşik yapı için çeşitli kısıtlar içermesi nedeniyle, daha gerçekçi bir tercih yapısı sunsa da istenilen sonuçları vermemektedir. Literatürde, ayrıca, daha gelişmiş modeller yer almasına rağmen, bu modeller pratik olarak uygulanabilirlikten uzaktır

Tez kapsamında üretilen tüm yayınlarda, Eskişehir Ulaşım Ana Planı Revizyonu işi kapsamında 2015 yılında Eskişehir'de toplanan hane halkı anketinden, zorunlu olmayan yolculuklara ait veriler kullanılmıştır. Zorunlu olmayan yolculuklara ait verilerin kullanılmasının temel nedeni, yolculuğa başlangıç zamanı, son nokta ve tür açısından tercih yapabilecekleri bir durumun incelenmesinin sağlanmasıdır. Ev-iş yolculukları gibi zorunlu yolculuklarda, değerlendirmeye alınan üç farklı konunun birkaçı veya tamamı için tercih yapılabilmesi söz konusu değildir.

Hane halkı anketlerinde, bireyler ve/veya haneler ile ilgili, aralarında gelir, yaş, hane büyüklüğü vb. çeşitli bilgilerin yer aldığı sosyo-ekonomik özellikler ve bireyler veya hanelerin, ulaşım türü seçimleri, seçtikleri türün yolculuk süresi ve maliyeti vb. günlük ulaşım alışkanlıklarına ait bilgiler toplanmaktadır. Hane halkı anketinde yer alan tüm farklı bilgiler, bu çalışmada bağımsız değişken olarak kullanılmak üzere değerlendirilmiştir. Tahmin edilen modellerdeki bağımlı değişkenler; ulaşım türü için özel otomobil, toplu taşıma ve yürüme, yolculuğa başlangıç zamanı için sabah zirve, zirve dışı ve akşam zirve saatler, son nokta için ise Eskişehir'de zorunlu olmayan yolculuklar için çekim noktası özelliği taşıyan, Espark ve Özdilek alışveriş merkezleri ile Arifiye Mahallesi'ndeki pazar seçilmiştir.

Çalışmanın kapsamını oluşturan, zorunlu olmayan yolculuklar ile ilgili olan ve tezde incelenen başlıca araştırma konuları aşağıda sıralanmıştır:

(1) Yolculuğa başlangıç zamanı, yolculuğun son noktası ve tür seçimleri hangi düzeyde ilişkilidir? Örneğin; belirli bir başlangıç zamanı ve/veya son nokta seçimi için bireylerin türlerle ilgili algıları nasıl şekillenmektedir?

(2) Bu üç seçimin arasındaki çapraz esneklik nedir/ne durumdadır? Örneğin; bir fiyatlandırma uygulaması ile ulaşım türü seçimine etkileyen unsurlardan birinin değiştirilmesi durumunda başlangıç zamanı ve/veya son nokta seçimleri nasıl değişmektedir?

(3) Kesikli olarak ifade edilen ve modellenen bu üç seçim için oluşturulan en iyi seçenek düzeni nasıl olmalıdır? Örneğin; birbirine yakın iki son nokta seçeneği gruplanmalı mıdır veya yolculuğa başlangıç zamanı için hangi saat aralıkları alınmalıdır?

Her bir modelin tahmin sonuçları her bir makalede irdelenmiş ve daha az gelişmiş yaklaşımlar (ÇTL ve HL) ile daha gelişmiş yaklaşımların (GSUD ve GHL) karşılaştırılması amacıyla model çiftleri arasında mantıksal ve istatistiksel değerlendirmeler yapılmıştır. Bu değerlendirmeler sonucunda; HL modellerin ÇTL modeline göre daha gerçekçi sonuçlar verdiği, GSUD modelinin HL modellerine göre, GHL modelinin ise tüm modellere göre daha üstün olduğu sonucuna ulaşılmıştır. Yayınlar ile ortaya konulan bu değerlendirme sonuçlarına göre, bu tez çalışması kapsamında geliştirilen GHL modeli, hem gerçek seçimleri ve davranışları daha iyi yansıtan sonuçlar vermesi hem de model performansı açısından en üstün model olarak belirlenmiştir.

GHL modelinin geliştirilmesi aşamasında; hiyerarşik bir yapıda olan söz konusu üç seçim için nasıl bir sıralama yapılacağı, diğer bir deyişle, hiyerarşinin farklı seviyelerinde hangi değişkenlerin yer alacağı ve hiyerarşinin farklı seviyeleri için farklı matematik bağıntılar gerekip gerekmediği konuları araştırılmıştır. Bu araştırma için seçimlerin hiyerarşisinin değişik şekillerde oluşturulduğu, hiyerarşinin seviyelerinin eksiltildiği (iki seçimin gruplanması yolu ile) veya hiyerarşiye seviye eklendiği (yeni bir seçimin eklenmesi veya üç ana seçimden birinin iki aşamalı olarak tanımlanması yoluyla) farklı model yapıları denenmiş ve bu yapılar sınanmıştır. Yapılan bu sınamalar ile gerek önerilen GHL modeli için ve gerekse hiyerarşik yapıda olan diğer tercih modelleri için kullanılabilecek sistematik bir yaklaşım ortaya konulmuştur.

Tahmin sonuçları ışığında, genellikle, bireylerin "hangi hareket saati", "hangi varış yeri" ve "hangi tür" kararlarını ortak bir değerlendirme sonucu aldığı belirlenmiştir. Buna karşılık, geleneksel dört aşamalı model, bu kararların tamamının ayrı ayrı alındığı varsayımını yapmaktadır. Öte yandan, ortak olarak alınan kararlar arasındaki bu ilişkinin göz ardı edilmesi durumunda, zaman değeri vb. sosyo-ekonomik göstergelerin hatalı olarak tahmin edildiği de görülmüştür. Bu durumun, yanlış ve uygun olmayan politika kararlarına yol açacağı açıktır.

Önerilen GHL modelleme yaklaşımı başlangıç zamanı, son nokta ve tür açısından sınırlı sayıda seçenek içeren orta ve küçük ölçekli planlama çalışmaları için uygundur. Bu yöntemin daha fazla sayıda seçenek içeren çalışmalarda da kullanılması mümkündür, ancak bu durumda modelin kullanılabilmesi için, kentte alt analiz bölgeleri oluşturulması ve GHL modelinin her alt bölge için ayrı ayrı hesaplanması daha sağlıklı sonuçlar verecektir. Ayrıca, önerilen yöntemin, günün farklı saatleri için daha gerçekçi başlangıç-son matrisleri vermesi de söz konusudur. Bu çalışmanın sağlaması amaçlanan diğer katkıları aşağıda sıralanmıştır:

(1) Bu çalışma ile talebin ve tercihlerin incelenmesi konusunda, yeterli düzeyde bilinmeyen ve/veya kullanılmayan, sistematik ve mevcutlardan daha gerçekçi bir modelleme yaklaşımı sunulmuştur.

(2) Sunulan modelleme yaklaşımı, karar vericilerin ürettikleri ulaşım politikaları için de değerli girdiler sağlayabilecektir. Bu yaklaşım sayesinde, ulaşım darboğazları için üretilen seçenekler ve politikalar, makro ölçekten çok daha ayrıntılı olarak ele alınabilecektir.

(3) Birçok disiplinde de kullanım alanı bulan, özellikle fizibilite çalışmalarının önemli bir girdisi olan zaman değeri vb. ulaşım ile ilgili ekonomik büyüklükler, önerilen modelleme yaklaşımı ile daha doğru ve hassas olarak hesaplanabilecektir.

#### **1. INTRODUCTION**

#### **1.1 Motivation**

Since 1940s, transportation planning studies became relying primarily on travel demand forecasting models (Johnston, 2004). However, the real interest of travel demand models has started in US at 1960s after the decision of "Federal-Aid Highway and Urban Mass Transportation" that aimed to connect financial aids for urban infrastructure and highway projects by performing a comprehensive transportation master plan. Consequently, the long-familiar four-step model has been established and extensively disseminated as the main modelling tool in most transportation planning studies (Boyce, 2002). This prevalence was associated with the simplicity of the four-step model when applying on regional-based planning horizons (Gu, 2004). However, some shortages associated with the sequence of steps, aggregate orientation, and the lack of considering characteristics of decision makers, put the four-step model under some criticism.

The four-step model is a trip-based travel demand model that is relying more on trips' characteristics and follows a pre-determined sequential procedure. In the first two steps (trip generation and trip distribution) the model uses land use data along with characteristics of transportation system (e.g. travel time) to produce "non-equilibrated" trip tables (origin-destination matrix). In the third step (modal split), independent from the first two steps, various characteristics of the travellers and travel modes' attributes are evaluated and calibrated to produce mode choice models. In the fourth step (trip assignment), the transportation network is loaded by the reproduced travel demand through the route choice process that considers only the network's characteristics and neglects any correlation with other choice dimensions such as departure time, destination and mode or weather to perform the trip at all (McNally, 2000). That leads to the four-step model failing to execute in most applicable policy tests that require detailed and specific analyses (McNally, 2000).

Over the years, various methods for the trip distribution step (the second step of the four-step model), have been developed to serve different modelling approaches (e.g. trip-based and activity-based models). For example, Growth Factor models adopt linear regression techniques to forecast future trips based on base-year trips. On the other hand, Gravity models and Intervening Opportunities models assume that trip distribution is explicitly related to trip resistance (e.g. travel time, distance and accessibility). Moreover, Trip Interchange models account explicitly for relative level of service of travel modes between the trip origin and trip destination. Finally, another type is Destination Choice models which represent individuals' destination choice process based on exogenous variables of attributes of alternatives and decision maker's characteristics.

Despite destination choice models show better performance in terms of goodness of fit and predictability over other traditional models (e.g. Gravity models), they seem to be similar in terms of the distribution theory. By words, both approaches ignore the potential correlation between destination choice and other travel dimensions that may exist inside the choice set within the same choice situation. For example, through congested networks, all destination distribution models assume compensations between closer destinations depending on the relative origin-destination impedance function (e.g.travel time). However, this assumption is violated by the actual travel behaviour of individuals. For example, in discretionary trips, individuals may shift their departure time or change the travel mode to keep traveling to their desired destinations or change destination to travel at proper time by specific travel mode. Thus, for such kind of trips, deeming the mutual interaction between destination choice from one side, departure time and travel mode choices from the other is a prerequisite in order to properly evaluate different policy measurements that aim to mitigate traffic congestion and accurately forecast their associated consequences. Worth mentioning, the inter-dependences between such travel demand dimensions can be sufficiently represented through advanced choice models rather than the traditional four-step model (Bhat, 1998).

From another hand, most researches that focused on the interaction between different travel dimensions (e.g. destination, departure time and travel mode) did ignore the potential inner-correlation that may exist between alternatives that belong to the same travel dimension (e.g. spatial correlation between closer destinations) (Hassan, 2017).

As there is a gap in literature about representing a unified choice model that connect different travel demand dimensions and consider various potential correlation of them, this research contributes filling this gap through introducing three research papers that employ some discrete choice models for representing three major travel dimensions which are; destination, departure time and travel mode. Such models contribute more to mathematical modelling literature of transportation demand models that also allows for more detailed and specific micro-policy analyses where traditional four-step model cannot. These detailed analyses can provide policy makers with very specific recommendations such as; value of time (VOT) based on travel mode, time of day and destination which can be used to estimate supply-demand functions dependent on time of day and destination, effective locations and times to apply congestion pricing and cordon pricing, best locations to apply different public transportation development measures, optimal locations and times to apply private car restriction measures, etc. Moreover, the value of cross-elasticity between any pairs of alternatives (i.e. simulation) will provide policy makers with the specific compensation between times, destinations and travel modes if a specific change in an independent variable is imposed (e.g. increasing travel cost).

#### **1.2 Purpose and Scope of the Dissertation**

The purpose of the dissertation is to model the inter-relationship (dependency) between departure time, destination and travel mode alternatives under a single unified framework in the context of discretionary home based or non-home based trips (e.g. home based shopping, non-home based shopping, home based recreational, etc.). This can be achieved through developing a number of discrete choice models that can incorporate different substitution patterns in order to identify the best model within them. Especially when detailed and specific analyses (micro-analyses) are required, these models can provide a better representation of the actual travel behaviour of individuals compared with the traditional four-step model while containing a similar level of mathematical simplicity. The proposed methodologies and examinations as a part of this dissertation are presented and published in three research papers; Figure 1.1 illustrates a chart that summarizes the main subject of each paper and expresses the relevance between them.

The first paper has been published in International Journal of Engineering. This paper mainly looks for ways to overcome the limitations associated with the concept of Irrelevant form Independent Alternatives (IIA) which is exhibited in traditional Multinomial Logit (MNL) models. In order to do so, the paper proposes a methodology that employs three-level Nested Logit (NL) approach to connect the three travel dimensions that allows different correlation structures. The proposed methodology provides a more reliable and flexible approach where each travel dimension can be placed at different nesting level with Gumbel distribution for error terms that have Identical Independent Distribution (IID) within the same nest or the same sub-nest. Moreover, inner-correlation in the same travel dimension (e.g. similarities between bus and tramway in the travel model travel dimension) can be represented at a specific nesting level.

## PAPER-1

Overcoming the limitations of Multinomial Logit models- Introduction of multidimensional correlation through using three-level Nested Logit models.

### PAPER-2

Overcoming the limitations of Nested Logit models- Introduction of spatial correlation through using Order Generalized Extreme Value models.

## PAPER-3

Modelling multi-dimensional correlation, spatial and temporal dependency and various heterogeneity through a novel modelling by using Generalized Nested Logit models.

Figure 1.1 : Published papers' main subjects and associated relevance.

The second paper is published in the Promet Traffic &Transportation journal. Opposite to conventional NL models that was introduced in the first paper, this paper assesses the effect of considering spatial correlation of adjacent discretionary destinations on the choice of the two other travel dimensions by using the Ordered Generalized Extreme Value (OGEV) approach. The paper embraces a hybrid ordering pattern in which different bases for the order of destinations can be adopted. That is, along with the conventional geographical location-based ordering, an average origindestination travel time-based ordering can be considered as well. Consequently, this approach can readily represent the heterogeneity in individuals' perceptions toward urban discretionary destinations while evaluating different departure times and travel modes.

Finally, the third paper, which is published in International Journal of Engineering, introduces a novel modelling methodology for using the Generalized Nested Logit (GNL) model to represent multi-dimensional potential correlations; between different travel dimensions (inter-correlation), inside the same travel dimension (inner-correlation) and correlation due to ordered nature travel dimensions (e.g. spatial correlation among destinations and temporal correlation between departure times). This paper builds upon the concept of moving away from traditional NL models and provides a comparison between the offered methodology and models examined in first two papers. Overall, the proposed GNL model has been found distinctly developed over the NL and OGEV approaches. Its simplicity along with the incomparable flexibility in representing a lot of correlation patterns within and among different travel dimensions have been demonstrated.

#### **1.3** Novelty of the Dissertation

In this dissertation, I propose the using of discrete choice modelling to examine departure time, destination and travel mode choices under a unified modelling structure for individuals' urban discretionary trips. Even though there are a lot of previous studies that focused on modelling multi-dimensional travel demand choices under different planning scopes (i.e. activity-based, trip-based and tour-based models), most of them have introduced joint models that connect only two travel dimensions (e.g. departure time with travel mode or destination with travel mode). Moreover, other

studies that examined the three dimensions together did ignore the potential correlation between and within dimensions. That is, they either model each dimension separately and account for interactions with other dimensions by imposing representable variables in the utility functions (Hassan et al, 2017), or connecting them by using simple choice models (e.g. MNL) that do not represent multi-correlation efficiently (see Bowman and Ben-Akiva, 2001). However, in this dissertation, the three travel dimensions are modelled under united framework and multi-dimensional correlation that represents the actual heterogeneity within population is considered.

The proposed methodology's unique contributions can be summarized as follows;

- Capturing the potential interdependences among the three important travel demand dimensions of discretionary trips; departure time, destination and travel mode choices.
- Incorporating the potential correlations within each dimension.
- Considering the ordered nature of both departure time and destination alternatives.
- Allowing for spatial correlation between destinations to be dependent on departure time and travel mode rather than assuming an identical correlation pattern across them.
- Capturing unusual correlation patterns between error terms that may be thoroughly specific, unexpected, and very difficult to be observed in the market.
- Representing a time of day-based trip-end distribution model that can produce extremely more accurate temporal origin-destination matrices.
- Unlike traditional four-step model, parameter estimates produced from the proposed methodology can provide significant indications which precisely reflect the real behaviour of individuals (especially for OGEV and GNL models). This can enormously help policy makers to reach to a solid perception about the effects of applying some policies/strategies to manage demand through different times of day and towards different destinations.
- The methodology is consistent with Maximum Likelihood estimation technique with maintaining closed-form of choice probability expressions.

Overall, this dissertation establishes the concept of temporal and spatial mode choice modelling that accounts for various kinds of correlations among these three significant dimensions as well as within the choice set of each individual dimension. The prominent model (in the third paper) may be considered as a significant milestone towards obtaining a consistent, efficient and integrated full-scale behavioural-model that can lie in all travel demand dimensions for various planning scopes.

## 1.4 The Organization of the Dissertation

This thesis is organized as follows. First chapter, the introduction, addresses the aim and scope of the thesis and expresses its contribution to previous literature. The succeeding chapters (from chapter two to chapter four) introduce the main sections of the published papers from the first paper to the third paper respectively. Table 1.1 summarizes the bibliographic details of each paper and addresses the information about the published journals. Chapter five presents the main conclusions and recommendations that have been reached in the published papers.

#		Details of Paper
	Paper Title	Application of Discrete Three-Level Nested Logit Model in Travel Demand Forecasting as an Alternative to Traditional Four-Step Model
	Authors	Mahmoud Elmorssy and Hüseyin Onur Tezcan
1	Туре	Journal Paper
	DOI	<u>10.5829/IJE.2019.32.10A.11</u>
	Publisher	International Journal of Engineering
	Indexation	Q2 (SCOPUS) and Emerging Source Citation Index (ESCI)
	Paper Title	Ordered Generalized Extreme Value Model as a Tool for Demand Modelling of Discretionary Trips
	Authors	Mahmoud Elmorssy and Hüseyin Onur Tezcan
2	Туре	Journal Paper
2	Publisher	Promet – Traffic & Transportation
	DOI	10.7307/ptt.v32i2.3214
	Indexation	Q2 (SCIMAGO), Q3 (SCOPUS) and Science Citation Index Expanded (SCIE)
	Paper Title	Modelling Departure Time, Destination and Travel Mode Choices by Using the Generalized Nested Logit Model: Discretionary Trips
	Authors	Mahmoud Elmorssy and Hüseyin Onur Tezcan
3	Туре	Journal Paper
	Publisher	International Journal of Engineering
	DOI	10.5829/IJE.2020.33.02B.02
	Indexation	Q2 (SCOPUS) and Emerging Source Citation Index (ESCI)

Table 1.1 : Bibliographic details of the published papers.



# 2. APPLICATION OF DISCRETE 3-LEVEL NESTED LOGIT MODEL IN TRAVEL DEMAND FORECASTING AS AN ALTERNATIVE TO TRADITIONAL 4-STEP MODEL<sup>1</sup>

## 2.1 Abstract

This paper aims to introduce a new modelling approach that represents departure time, destination and travel mode choice under a unified framework. Through it, it is possible to overcome shortages of the traditional 4-step model associated with the lack of introducing actual travellers' behaviours. This objective can be achieved through adopting discrete 3-level Nested Logit model that represents different potential correlation (cross elasticity) among departure time, destination and travel mode alternatives. The proposed model has been estimated and tested by using discretionary trips' data from Eskisehir city, Turkey. In the light of the estimation results, individuals tend to jointly decide on discretionary travel dimensions rather than separately as assumed by the traditional 4-step model. Moreover, the proposed approach shows more flexibility in considering attributes of alternatives along with characteristics of decision makers. That results in a more behavioural travel demand modelling, more accurate future forecasting and more trusted policy implications. The proposed model represents a more accurate and reliable alternative for the first 3-steps of the traditional 4-step model in small-scale planning issues. Finally, the proposed approach is a significant milestone toward obtaining a consistent, efficient and integrated full-scale behavioural-model that consists of all travel demand dimensions.

<sup>&</sup>lt;sup>1</sup> This chapter is based on the paper "Application of Discrete 3-level Nested Logit Model in Travel Demand Forecasting as an Alternative to Traditional 4-Step Model", International Journal of Engineering (IJE), IJE TRANSACTIONS A: Basics, Vol. 32, No. 10, (October 2019) 1416-1428.

#### 2.2 Nomenclature

U	Total random latent utility function	β	Vector of coefficients for decision maker's characteristics
V	Deterministic component of the latent utility	3	Error term or random component unknown to the analyst
ASC	Alternative specific constant	°3	Error term associated with a specific nesting level
Q	Vector of alternative's attributes	θ	Scale parameter of an Extreme Value Distribution
С	Vector of decision maker's characteristics	η	Allocation Parameter of an Extreme Value Distribution
Т	Choice set of departure time alternatives	Subscr	ipts
D	Choice set of destination alternatives	tdm	Joint choice of a departure time "t", destination "d" and travel mode "m"
Μ	Choice set of travel mode alternatives	uen	Joint choice of a departure time "u", destination "e" and travel mode "n"
P[·]	Probability of choosing a specific alternative	xyz	Joint choice of travel dimensions "x", "y" and "z"
Pr[·]	Probability of achieving specific conditions	i	A decision maker
Greek	Symbols	y x	Choosing travel dimension "y" given another travel dimension "x"
α	Vector of coefficients for alternative's attributes	z y,x	Choosing travel dimension "z" given travel dimensions "y" and "x"
	anemative s attributes		traver dimensions y and x

## **2.3 Introduction**

Rapid growth in the world population has resulted in tremendous need for modern transportation demand strategies (Sumia and Ranga, 2018). However, demand prediction is a very crucial aspect that effects directly its management policies (Ghasemi and Rasekhi, 2016). The need for travel demand forecasting models as a base of transportation planning has been starts in 1940s (Johnston, 2004). By 1960s, travel demand models have been obtained extreme interest in US after the decision of Federal-Aid Highway and Urban Mass Transportation of restricting financial aid to infrastructure and highway projects in urban areas only if they were established on comprehensive transportation master plans (Morehous, 1969). As a result, the well-known four-step model has been developed and widely spread until becomes the main core and brain of most transportation planning studies (Boyce, 2002). The wide acceptance of four-step model is obtained due to its simplicity when applied on regional-based (large-scale) planning horizons (Gu, 2004). However, the shortages

associated with the fixed sequence, aggregate representation as well as the lack of behavioural considerations made the 4-step model being under uninterrupted criticism.

From another hand, considering the influences of departure time (or time of day in some literature) on individuals' travel demand is a prerequisite in order to properly evaluate different policy measurements that aim to mitigate traffic congestion to accurately forecast their associated consequences (Ghasemi and Rasekhi, 2016). However, the traditional 4-step model does not sufficiently cover the inter-dependences between departure time and different travel demand dimensions (Bhat, 1998).

Disregarding the time of day while modelling travel choices results in improper models because; (1) such models cannot provide precise estimates of travel choices during different times of day (Bhat, 1998), (2) via these models, the anticipated future shifts in trip departure times associated with potential future urbanization cannot be identified. (3) these models do not have the ability to evaluate different policies that aim to achieve significant shifts in travels' departure time such as dynamic congestion pricing control schemes (Setak et al, 2015; Weiner and Ducca, 1996; Stopher 1993).

This research aims to propose a trip-based travel demand model that considers for departure time, destination and travel mode choices under a discrete unified choice framework rather than the independent aggregate nature of traditional 4-step model. Such a model can provide a more effective and accurate alternative for travel demand prediction in different transportation planning objectives. By words, the correlations among the three considered travel dimensions (departure time, destination and travel mode) are represented through developing a 3-level Nested Logit (NL) model that can consider for different elasticity patterns and correlation structures. The reliability of the proposed model has been tested through applying on shopping and entertainment trips data which extracted from a household survey that was conducted in Eskisehir city, Turkey, at 2015, in the context of Eskisehir master plan project.

#### 2.4 Background

The analysis of transportation systems lays primarily on travel demand forecasting which interests in understanding the behaviour of decision makers (Ben-Akiva and Lerman, 1985). From 1960s till now, travel demand modelling is prevailed by the well-known 4-step model. Nowadays, the applications of 4-step model are almost universal

in most of aggregate trip-based analysis (e.g. master plans) (McNally, 2000). However, despite the wide usage of it, the 4-step travel demand forecasting model is associated with some serious drawbacks which may be summarized in the following points;

- Splitting the decisions within a trip into fixed steps (e.g. generation, distribution, mode choice and assignment) is far away from the actual individual decision-making rule (Oppenheim, 1995).
- Neglecting the effects of decision makers' characteristics in most steps leads to lack of human behavioural considerations which results finally in inaccurate future forecasting (Vuchic, 2005).
- The aggregate nature of 4-step model is more convenient for macro-scale analysis (e.g. regional-based analysis), however, when turning to micro-scale analysis (e.g. individual travellers-based), the model losses its consistency and effectiveness and lead to inaccurate outcomes (Vuchic, 2005).
- The deterministic approach assumed for some models leads to untrusted representation and does not allow for testing different hypothetical scenarios (Donnelly, 2010).
- The traditional 4-step model does not consider for the influences of congestion on the travel time in any of its steps (Johnston, 2004; Oppenheim, 1995), which underestimates the effects of congestion on passenger vehicle travel costs (Boyce, 2002).
- Most trip distribution models (e.g. gravity model), neglect the existence of some trip purposes at different time of day (Vuchic, 2005). For instance, the home-based work trips occur only at morning peak periods.

From another hand, the importance of departure time of trip (time of day) decision comes from the need to better understand the inter-relationship between congestion and trips distribution over time.

In the context of time representation approaches, while some studies have developed discrete choice-based departure time models others have adopted the continuous representation through different modelling techniques such as; Mutinomial Logit (MNL), Nested Logit (NL), Cross Nested Logit CNL, Paired Combinatorial (PC), Generalized extreme value (GEV), Ordered Generalized extreme value OGEV, etc. For example, Small (1979) has introduced a discrete time-of-day model that allocates

activity's time for work trips. Similarly, Hendrickson et al. (1984) have examined the flexibility of work trips departure times through a discrete Logit model of simultaneous travel mode and departure time interval choice. Moreover, Wilson (1989) has analysed costs of off-peak work schedules by estimating a discrete joint travel mode/work-start time choice model. Also, Noland and Small (1995) have developed an uncertainty travel time cost model, in which commuters choose discrete departure time that minimize an expected cost function. For discretionary trips, Bhat (1988) has developed a joint travel mode and departure time discrete choice model by using a hybrid MNL-OGEV approach.

In contrast, under continuous departure time approach, some studies have examined departure time through limited period of the day (e.g. morning trips departure time) by employing a proportional hazard duration model (Hamed and Mannering, 1993; Abu-Eisheh and Mannering, 1989). However, Bhat and Steed (2002) have developed a continuous departure time model with the entire day as a time frame by using a hazard-based model that adopts time-varying exogenous covariates and considers a heterogeneity for the unobserved attributes distributed among individuals.

From another hand, under the umbrella of activity-based modelling, some scholars have examined the effects of departure time choice on the daily activity pattern preferences. For instance, Wang (1996) has connected the timing utility of people's daily activities with travel time to account for heterogeneity associated with a specific activity over the course of the day. Moreover, to evaluate the effects of different congestion pricing schemes on driver behaviour, Yamamoto et al (2000) have proposed an activity based model that represents time allocation, departure time choice and route choice when a congestion pricing scheme is implemented on toll roads. Similarly, Ettema and Timmermans (2003) have modelled trip departure time in the context of activity scheduling behaviour. That is, their model accommodates the interdependence between trip departure time and activity time allocation. However, their model does not consider the unobserved heterogeneity (i.e. error term). The need for considering of unobserved heterogeneity comes from the fact that there are some variables which affect the choice of individuals but cannot be captured by the analyser (Ettema and Timmermans, 2003). Furthermore, a Multiple Discrete Continuous Extreme Value Model (MDCEV) have introduced in and developed by Bhat (2005 and 2008) in order to model activity's time allocation decisions. In this model, Bhat has

represented activity participation decisions in a discrete framework while formulates the duration spent for each activity in a continuous fashion. The model that is proposed by Bhat has been improved by Pinjari and Bhat (2010) to capture similarity within alternatives and involve departure time decisions of different activities.

From a tour-based modelling viewpoint, Bowman and Ben-Akiva (2001) have proposed a model that accommodate for mode choice side by side with temporal and spatial choices under the context of tour-based modelling approach. They have introduced an integrated disaggregate discrete choice activity model system that can generate time and mode specific trip matrices for forecasting. This model system involves five sub-models each represents different tour dimension and all sub-models are jointly connected through a simple two levels nested structure. Notably, in this model, time of day alternatives are not directly connected with travel mode and destination choices. Rather, they are connected indirectly through the log-sum parameters which are common in the higher level. Moreover, Garikapati et al. (2014) have analysed the effect of time on trip chaining through a tour-level joint model of activity's engagement, stops and timing.

Under the trip-based approach, Bhat (2008 and 1998a) has studied the interdependency between time of day and transportation mode choices through developing a discrete nested (MNL-OGEV) model. The model proposed by Bhat did not consider destination choices along with departure time and mode choices. However, generally for discretionary trips and particularly for shopping and entertainment trips, individuals are more likely to change destination with or without shifting their departure times and therefore, destination alternatives should be involved in the choice set of the model.

Worth mentioning, most of studies that account for the joint representation of multiple travel dimensions (e.g. departure time, destination, travel mode, etc.) have used Nested Logit model approach of McFadden (1978) to connect various dimensions. The privilege of NL model over other approaches is that, it results in closed form expressions for choice probability. That is, even if other approaches (that may account for correlations between error terms) consistent with Maximum Likelihood Estimation method, they do not result in closed form probability formulas. Rather, most of them (e.g. the Heteroskedastic Logit, Mixed Probit) require simulation-based estimation process which leads to a cumbersome analysis (Pinjari and Bhat, 2010). Nevertheless,

introducing alternatives through NL models enables analysts to impose "to some extent" the potential correlation structure among alternatives within mutually exclusive nests of the choice set and keeps on the closed-form of probability expressions.

From another point of interest, the importance of using choice models to represent departure time along with destination and travel mode arises from the essential need of introducing the actual travellers' behaviour while deciding simultaneously on these three crucial travel dimensions. This representation will result in more reliable demand models and better helps transportation planners who recently rely much on managing demand rather than increasing supply while facing urban congestion problems (Jrew et al. 2019). As illustrated by Basim Jrew et al. (2019), a successful Travel Demand Management (TDM) strategy depends directly on the extent of travellers' acceptance of it. For example, they have observed that individuals of Amman (Jordan) accept ridesharing strategies over congestion pricing schemes. Such behaviour can be easily predicted if a precise travel demand model that connects related travel dimensions is existed. Another example for the grandness of using joint travel dimensions choice models is the policies that encourage the using of clear transportation modes such as electric vehicles. That is, better understanding of inter-dependencies between destinations, usage of electric vehicle over time of day can lead to optimal distribution for recharging points along with better regulation of network voltages at peak traffic.

Another significant advantage of joint choice models over traditional four-step model is that they can examine the mutual influences of various factors that may jointly affect different travel dimensions. For example, besides conventional factors (e.g. travel time, travel cost, etc.) Shafiei et al (2018) have identified a wide range of variables that significantly affect the selection of travel mode. They have concluded that variables such as traffic avoidance, accessibility, land use, capacity and air pollution are important travel mode selection criteria. However, most of these variables are more likely affect the selection of other travel dimensions such as departure time and destination of trips. While traditional four-step model cannot provide a simultaneous effect of such variables on the three travel dimensions, joint choice models can perfectly do.

#### 2.5 Description of the Proposed Model

This research represents all of departure time (time of day), destination and travel mode choices under a unified model through using 3-level NL model in order to represent an effective and more accurate alternative approach for the first three steps in the 4-step travel demand model (generation, distribution and modal split). NL model is a disaggregate-based discrete choice model that relaxes the IIA property in MNL model by accounting for the correlation of error terms among similar alternatives (Koppelman and Bhat, 2006). To attain that, number of 3-level nesting structures that may describe the structure of the error distributions for alternative utilities has been developed. Figure 2.1 shows the general framework of the proposed model.

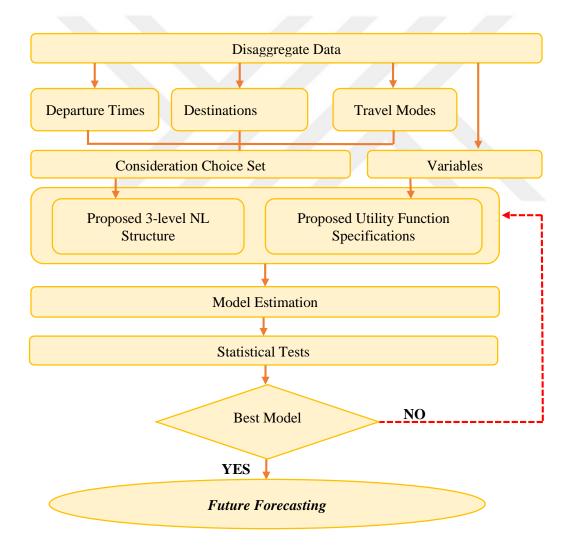


Figure 2.1 : General framework of the proposed approach.

In order to test the significance of the proposed model, a simple MNL model that assumes identical cross-elasticity among all possible combinations is proposed to be estimated.

For MNL model, equations 2.1 and 2.2 represent the general form of the total random utility function associated with alternatives.

$$U_{i,tdm} = V_{i,tdm} + \mathcal{E}_{i,tdm}$$
(2.1)

$$V_{i,tdm} = ASC_{i,tdm} + \beta_Q * Q_{i,tdm} + \beta_C * C_i$$
(2.2)

We assume an independent identical extreme value distribution (Gumbel Type I) for the error terms  $\mathcal{E}_{tdm}$  with scale parameter  $\theta$  and allocation parameter  $\eta=0$  (For the sake of simplicity, the abbreviation "i" has been dropped from the rest of the text). Thus, joint probability can be expressed as shown in equations 2.3 and 2.4.

$$P[tdm] = Pr [V_{tdm} - V_{uen} \ge \varepsilon_{uen} - \varepsilon_{tdm}], \qquad \forall [u \in T, e \in D \text{ and } n \in M]$$
(2.3)

where; 
$$\operatorname{Var}(\mathcal{E}_{tdm}) = \frac{\pi^2 \theta^2}{6}$$
 (2.4)

Therefore equation 2.5 can represent the probability function of choosing travelling at departure time "t" to destination "d" using mode "m" from the choice set of T\*D\*M alternatives is:

$$P[tdm|TDM] = \frac{1}{1 + \sum_{u,e,n}^{T,D,M} \exp\left(\frac{V_{uen|TDM} - V_{tdm|TDM}}{\theta}\right)},$$
(2.5)  

$$\forall [u \in T, e \in D \text{ and } n \in M]$$

According to above equation, in MNL model, just difference between deterministic utility functions is matter and thus, it is possible to normalize scale parameter to the unity (Equation 2.6).

$$P[tdm|TDM] = \frac{1}{1 + \sum_{u,e,n}^{T,D,M} \exp(V_{uen|TDM} - V_{tdm|TDM})},$$

$$\forall [u \in T, e \in D \text{ and } n \in M]$$
(2.6)

In NL models, alternatives that are more similar in attributes and characteristics are grouped (or nested) with each other and formed exclusive subsets (nests). That means; alternatives in the same nest have a higher level of similarity and competitiveness than alternatives in different nests. Statistically, this can be achieved by imposing a random component (error term) to be common for all alternatives in the same nest and differs within nests. Such a random component ensures identical cross elasticity for all pairs of alternatives only in the same nest (subset) rather than being identical for all pairs of alternatives in the choice set like MNL model. Any potential correlation structures between groups of alternatives can be represented through developing associated nesting structures (tree structure).

Therefore, in order to properly represent the correlation between departure time, destination and travel mode, a set of proposed 3-level nesting structures have to be constructed. In which, each travel dimension can be settled at a specific level with Gumbel distribution for error terms that is IID within the same nest or the same subnest. For instance, departure time alternatives may be located at the highest level, destination alternatives may be placed at mid-level and travel mode at the lowest one. This structure can be interpreted by assuming that, individuals are firstly decide on at which time to travel and therefore, they determine to which destination and finally they choose the travel mode. Moreover, on the context of correlation, this structure assumes similarity between alternatives belong to the same departure time nest. Intuitively, this assumption is accurate if time of day affects significantly and equally the unobserved attributes associated with destinations and modes such as safety and comfort. Moreover, inner-correlation in the same travel dimension (e.g. similarities between public transportation modes in the travel mode) can be represented at a specific level, travel dimension itself at another and combinations of the other two travel dimensions placed at the third level.

In order to express the probability functions associated with the proposed 3-level NL structures; we assume a 3-level nesting structure where different trip dimensions (x, y and z) can be located at different levels (Figure 2.2). Based on Figure 2.2, equations 2.7 and 2.8 can represent the general forms of the utility functions associated with elementary alternatives;

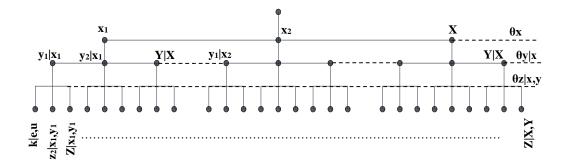


Figure 2.2 : A proposed nesting structure for connecting x, y and z by three-level NL model.

$$U_{z|x,y} = V_{z|x,y} + \mathcal{E}_{x} + \mathcal{E}_{y|x} + \mathcal{E}_{z|y,x}$$
(2.7)

$$V_{z|x,y} = ASC_{z|x,y} + \beta_Q * Q_{z|x,y} + \beta_C * C_i$$

$$(2.8)$$

Equations 2.9, 2.10 and 2.11 show the variance of error terms at level 1, 2 and 3 respectively.

$$\operatorname{Var}(\mathcal{E}_{z|y,x}) = \frac{\pi^2 \theta_{z|y,t}^2}{6}$$
(2.9)

$$\operatorname{Var}(\mathcal{E}_{y|x}) = \frac{\pi^2 \theta_{y|x}^2}{6}$$
(2.10)

$$\operatorname{Var}(\mathcal{E}_{x}) = \frac{\pi^{2} \theta_{x}^{2}}{6}$$
 (2.11)

Consequently, the general forms of the joint probability of choosing x, y and z from a choice set of X\*Y\*Z alternatives can be expressed through equation 2.12, 2.13 and 2.14.

$$P[xyz] = P[x] P[y|x] P[z|y,x]$$

$$= \frac{\exp\left(\frac{\theta_{y|x}}{\theta_{x}}I_{y|x}\right)}{\sum_{h}^{x} \exp\left(\frac{\theta_{y|x}}{\theta_{x}}I_{y|h}\right)} * \frac{\exp\left(\frac{\theta_{z|y,x}}{\theta_{y|x}}I_{z|y,x}\right)}{\sum_{j|x}^{Y|x} \exp\left(\frac{\theta_{z|y,x}}{\theta_{y|x}}I_{z|j,x}\right)} * \frac{\exp\left(\frac{V_{z|y,x}}{\theta_{z|y,x}}\right)}{\sum_{j|y,x}^{Z|y,x} \exp\left(\frac{V_{f|y,x}}{\theta_{z|y,x}}\right)}$$
(2.12)

where, 
$$I_{y|x} = \ln \sum_{j|x}^{Y|x} \exp\left(\frac{\theta_{z|y,x}}{\theta_{y|x}} I_{z|j,x}\right),$$
 (2.13)

. .

$$I_{z|y,x} = \ln \sum_{f|y,x}^{Z|y,x} \exp\left(\frac{V_{f|y,x}}{\theta_{z|y,x}}\right)$$
(2.14)

One of the most key features of the proposed approach over the traditional 4-step model is considering decision makers' characteristics while modelling destination choice. Clearly, neglecting the socio-demographic characteristics of travellers can lead to insufficient models which cannot deal with the potential dynamics during the different planning horizons (McNally, 1997).

The variables  $I_{y|x}$  and  $I_{z|y,x}$  has a very important interpretation. In literatures, it is referred to by various terms; Inclusive Value "IV", Log-Sum, Expected Maximum Utility "EMU", or Expected Consumer Surplus "ECS". We consider the term inclusive value IV in the context. IV represents average utility which obtained by population in case of choosing any alternative within the specific nest. The existence of scale parameter  $\theta_{z|y,x}$  or  $\theta_{y|x}$  in the denominator of IV equation is the source of similarity between alternatives within a nest. By word, different scale parameters among nests lead to different IV's which leads to different cross elasticity between those nests. Moreover, as scale parameter decreases IV increases and thus the sensitivity of choosing alternatives in that nest is more than choosing alternatives in other nests. That leads to a higher cross elasticity for alternatives with higher correlation.

From another hand, as MNL model, for any level of the NL model, difference between utilities is the only determinant of probabilities. Therefore, it is possible to normalize one of the three scale parameters to be equal to one and estimate the others. While normalization decreases some computational burdens in the estimation process, it eases however, the interpretation and testing statistics of the estimated scale parameters. That is, in three-level NL model, assuming one scale parameter to be equal to one makes the other parameters confined in specific range to be acceptable intuitively and statistically. For example, if the overall scale parameter at top level is assumed to equal one, the scale parameters of the mid-level must be less than or equal to one to assure that the overall variance is more than or equal to the variance of error terms of sub-nests. Consequently, since the variance of mid-level should be more than or equal to the variance of lowest level, the scale parameters of the lowest level should be less than or equal to the scale parameter at mid-level. The opposite is right, where if the scale parameter of elementary alternatives is assumed to equal one, then the scale

parameter of up-levels must be more than or equal to one. Moreover, under all conditions the values of scale parameter have to be non-negative to assure a concave single optima maximum likelihood function. In this research, we adopt the first setting through normalizing the scale parameter at top level to one. Therefore, the probability function takes the form of equation 2.15.

$$P[xyz] = \frac{\exp(\theta_{y|x}I_{y|x})}{\sum_{h}^{X}\exp(\theta_{y|x}I_{y|h})} * \frac{\exp\left(\frac{\theta_{z|y,x}}{\theta_{y|x}}I_{z|y,x}\right)}{\sum_{j|x}^{Y|x}\exp\left(\frac{\theta_{z|y,x}}{\theta_{y|x}}I_{z|j,x}\right)} * \frac{\exp\left(\frac{V_{z|y,x}}{\theta_{z|y,x}}\right)}{\sum_{j|y,x}^{Z|y,x}\exp\left(\frac{V_{f|y,x}}{\theta_{z|y,x}}\right)}$$
(2.15)

where,  $0,00 \le \theta_{z|y,x} \le \theta_{y|x} \le 1,00$ 

## 2.6 Case Study

In this paper, the proposed model will be estimated and calibrated by using shopping and entertainment trips data of Eskisehir city, Turkey. Notably, several studies have directed their attention toward examining different aspects of compulsory trips (work trips) rather than shopping and entertainment trips. Obviously, they were motivated by the demonstration of commuter trips on the daily congestion (Mahmassani and Jou, 1998). However, some other little literatures have directed their studies toward examining individuals' behaviour while performing discretionary trips (Steed and Bhat, 2000). We adopt the second framework of studying shopping and entertainment trips as discretionary trips due to the following reasons;

- Discretionary trips establish a considerable proportion of the total daily trips with speculations predict a growing contribution to traffic congestion and mobile source emissions (Gordon et al, 1988).
- Among evening peak-period trips, discretionary trips are found to occupy the first grad between all other trip purposes (Salkind, 2014).
- Discretionary trips' departure times and destinations are more likely to be shifted by individuals than work trips which have a more restricted time and space spans. In other words, compulsory trips (e.g. work trips) have less flexibility to make a change in departure time and destination.

The considered shopping and entertainment trips data are a part of large-scale revealed preference data which were collected through a household survey in 2015 in the

context of Eskisehir master plan project which operated by Eskisehir Metropolitan Municipality. From approximately 10,000 households in the city, variety of data has been obtained. These data include;

- 1. Household socio-demographics (household size, income, and vehicle ownership),
- 2. Individual socio-demographics (gender, age, license holding to drive, and employment status),
- Individual's travel information (departure time(s), purpose of the trip(s), origin(s) and destination(s))
- 4. Attributes of used transportation mode(s) (out of vehicle travel time, in vehicle travel time and fare).

The total number of observations was around 30,000 of which about 12,000 observations are related to discretionary trips distributed among different departure times, destinations (about 190 destinations) and travel modes (10 modes; car, public bus, tramway, minibus, taxi, service, motorcycle, bicycle, walk and other). In this research, we focus our analysis on entertainment and shopping trips with specific number of times of day, destinations and transportation modes. By words, for those who travel to shopping and entertainment trip, time of day has been categorized into three different groups that differ among each other in terms of traffic conditions and availability of individuals' free times; peak time trips (p) [morning-peak 7.00am and 9.00am, and noon-peak 4.30pm and 6.30pm], off-Peak time trips (o) [9.00am and 4.30pm] and Evening time trips (e)[6.30pm up to 10.00pm]. Notably, observations outside these three periods have been neglected since they are trivial and happen after mandatory closing hours of shopping and entertainment places (i.e. 10.00 pm). On the other hand, by considering only entertainment/shopping trips, the most attracted destinations are observed in three central areas which distinguished by having a lot of retail and entertainment activities. These destinations are; Espark shopping centre (s), Ozdilek shopping centre (z) and Local Bazaar (l) as illustrated in Figure 2.3. In the context of transportation mode, three modes that access to the three destinations and available during the three times of day have been considered in our analysis. These modes are private car (c), public bus (b) and tramway (tr). Eventually, by determining the choice set of each travel dimension available for each individual, the total number of observations has been found to be 529 observations. The distribution of individuals among available alternatives of each choice subset is shown in Table 2.1.

Regarding the preferences of time, surprisingly, more than half of observations (52.36%) were found preferring off-peak time period (9.00 am – 4.30 pm) to achieve their recreation trips. However, this result is consistent with the high portion of non-workers/ housewives in the sample which reaches 53.12% as illustrated in Table 2.2. On the other hand, about 28% of individuals prefer evening time to execute their shopping and entertainment activities. Obviously, they choose to go after normal work hours with enough amount of time to avoid congestion associated with commuter trips. Furthermore, individuals are less likely to choose peak periods to make their discretionary trips (only 19.66%). This result reflects the non-obligatory nature of discretionary trips without specific limitations in departure times which leads individuals to avoid high traffic volumes associated with peak periods.

Examining destination choices expresses that, in Eskisehir city, individuals who want to accomplish shopping or entertainment activities will most likely travel towards Bazaar region or Espark shopping centre (38.4% and 34.8% respectively) while Ozdilek shopping centre is less likely to be chosen (26.8%). Remarkably, while individuals travel to perform discretionary trips, distance between origin and destination isn't the most significant factor that affects the distribution of trips among destinations. In our case, reviewing average distances between each trip origin and the chosen destination of each individual leads to the same result (Table 2.3). That is, despite Espark has the longest average travel distance from travel origins (5.10 Km), it attracts considerable share of trips like Local bazaar which has the lowest average travel distance (4.00 Km). At the same time, average travel distance from trip origins to Ozdilek is 4.10 Km which near to the distance to Bazaar, however, individuals are less likely traveling to it. Other factors such as travel time, travel cost, accessibility, density of shopping and entertainment activities are more crucial while deciding on destination of discretionary trip. Of course, some of these factors could be examined through the proposed nested model. Notably, this is a core benefit for the proposed approach over the conventional 4-step model where actual individuals' perceptions toward characteristics of alternatives are used rather than the average values. That results in more behavioural-based forecasting models which leads to more accurate future policy implications.

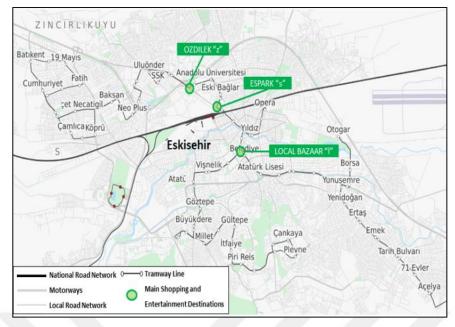


Figure 2.3 : Map of the study area.

**Table 2.1 :** Sample distributions among alternatives.

		# of Observations	Rate (%)
	Peak (p)	104	19.66
Departure time (t)	Off-Peak (o)	277	52.36
	Evening (e)	148	27.98
	Espark (s)	184	34.78
Destination (d)	Local Bazaar (l)	203	38.37
	Ozdilek (z)	142	26.84
	Car (c)	116	21.93
Travel modes (m)	Bus (b)	98	18.53
	Tramway (tr)	315	59.55

	# of Observations	Rate (%)
Doesn't work or housewife	281	53.12
Works or a student	248	46.88

Table 2.3 : Average travel distance to the destinations.

Row Labels	Average Distance (Km)
Espark (s)	5.1
Local bazaar (l)	4.0
Ozdilek ( <b>z</b> )	4.1

Finally, the modal split of shopping and entertainment trips is 21.9%, 18.5% and 59.6% for car (c), bus (b) and tramway (tr) respectively. More than half of individuals do prefer tramway over other modes while traveling to discretionary trips. However,

this distribution is totally different when comparing with modal split of work trips which is 63%, 15% and 22% for car, bus and tramway respectively. Obviously, individuals' behaviour while choosing among travel modes is strongly correlated with trip purpose since other factors may be included while decide traveling to shopping places such as availability of parking places, parking fees, activity time, flexibility of both departure and arriving times, etc. Such factors and more can be examined and investigated by representing it through the utility functions of alternatives.

#### 2.7 Models Estimation

The total number of alternatives equals 27 (the possible combinations of 3 times [p, o, e], 3 destinations [s, l, z] and 3 transportation modes [c, b, tr]). Additionally, linear in parameters utility functions have been assumed which consider total travel time TT and total travel cost TC as alternative's attributes and monthly income group INC, age AGE, car ownership COW (dummy variable) and student status SS (dummy variable) as socio-demographic characteristics of individuals.

Furthermore, in order to check the multi-collinearity, the correlation among all variables has been calculated (Pearson correlation coefficients). Table 2.4 shows the correlation matrix of the variables. As illustrated, the correlation between all pairs of the variables is low (weak) except for age-student status where correlation has a moderate (intermediate) value (Elmorssy and Tezcan, 2019). Therefore, all proposed variables can be used efficiently to estimate the proposed models.

	TT	TC	COW	INC	AGE	SS
TT	1					
TC	-0.05	1				
COW	-0.06	0.18	1			
INC	-0.05	-0.002	0.21	1		
AGE	-0.06	-0.01	0.12	0.05	1	
SS	0.05	-0.16	-0.1	-0.1	-0.60	1

**Table 2.4 :** Correlation matrix of the proposed variables.

Moreover, for all proposed nesting structures, in the light of descriptive statistics, different specifications for the available variables have been introduced in order to capture the best model for each structure in terms of the magnitude of inclusive value parameters, signs and degree of significance of parameters as well as the overall goodness of fit of the model. That is, for each proposed structure, different combinations of generic and alternative specific variables have been assumed. Notably, representing alternative specific parameters means a total number of parameters equal to the total number of alternatives (total number of alternatives minus one, in our example equals 26). Introducing this large number of estimates will not only add more encumbrances in estimation process but also complicate the interpretation of the results. Therefore, in an attempt to intuitively interpret results of estimation as well as ease the estimation process, the alternative specific variables (especially those related to individual characteristics) have been represented to be particular to a specific travel dimension(s) rather than the all 27 alternatives. For instance, in some specifications, the parameter of age variable has been presumed to be specific to destination or transportation mode alternatives and therefore, best specifications that lead to best models are selected.

#### **2.8 Discussion of Estimation Results**

In order to properly represent the correlation between time of day, destination and transportation mode, a set of the proposed 3-level nesting structures is estimated. In which, each travel dimensions could be settled at a specific level with Gumbel distribution for error terms that are IID within the same nest or the same sub-nest. Moreover, inner-correlation in the same travel dimension (e.g. similarities between bus and tramway in the transportation model travel dimension) can be represented at a specific level. For all proposed nesting structures, the scale parameters at upper level have been normalized to 1.00. In the light of the estimation process, 4 proposed 3-level NL structures have been found representing acceptable estimates with remarkable goodness of fit. The best 4 models are appointed as NS-1, NS-2, NS-3 and NS-4. Notably, these models are associated with the same utility function specifications which are illustrated in equation 2.16. Furthermore, Table 2.5 shows the estimation results of the four proposed NL structures.

$$V_{t,d,m} = ASC^{m} + b_{TT}^{t} * TT + b_{TC} * TC + b_{COW}^{m} * COW + b_{INC}^{d} * INC + b_{SS}^{m} * SS + b_{AGE}^{t} * AGE \qquad (2.16)$$

	MNL	NS-1	NS-2	NS-3	NS-4
Constants					
Car Specific Alternatives	$-3.30(-7.23)^{a}$	-10.30 (-3.02) <sup>a</sup>	-5.90 (-2.80) <sup>a</sup>	-7.27 (-3.80) <sup>a</sup>	$-4.39(-3.25)^{a}$
Bus Specific Alternatives	-1.18(-10.05) <sup>a</sup>	$-3.60(-3.40)^{a}$	-1.94 (-3.01) <sup>a</sup>	$-1.78(-9.5)^{a}$	$-1.82(-9.00)^{a}$
Tram Sp. Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
<u>Total Travel Time</u>					
Peak Specific Alt.	$-0.014(-3.95)^{a}$	-0.076 (-2.90) <sup>a</sup>	$-0.03(-2.44)^{a}$	$-0.022(-4.0)^{a}$	-0.021 (-1.86) <sup>b</sup>
Off-peak Specific Alt.	$-0.009(-1.98)^{a}$	-0.018 (-2.50) <sup>a</sup>	$-0.018(-2.25)^{a}$	$-0.022(-3.61)^{a}$	-0.020 (-2.93) <sup>b</sup>
Evening Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Total Cost (Generic-TL)	$-0.11(-2.30)^a$	-0.42 (-5.70) <sup>a</sup>	-0.10 (-1.85) <sup>b</sup>	-0.41 (-5.0) <sup>a</sup>	-0.28 (-3.81) <sup>a</sup>
<u>COW (0&amp; 1)</u>					
Car Specific Alternatives	3.17 (6.77) <sup>a</sup>	9.50 (2.94) <sup>a</sup>	5.70 (2.70) <sup>a</sup>	6.00 (3.33) <sup>a</sup>	3.32 (3.98) <sup>a</sup>
Bus Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Tram Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Income (1000TL/ Month)					
Espark Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Local Bazaar Sp. Alt.	0.06 (1.66) <sup>b</sup>	0.00 (F)	0.00 (F)	0.00 (F)	0.09 (1.72) <sup>b</sup>
Ozdilek Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Student Status (0& 1)					
Car Specific Alternatives	- 1.42 (-3.74) <sup>a</sup>	$-4.02(-2.30)^{a}$	$-2.08(-2.05)^a$	$-3.52(-3.1)^a$	- 1.58 (-2.71) <sup>a</sup>
Bus Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Tram Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Age (Years old)					
Peak Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Off-peak Specific Alt.	$0.022 (5.62)^a$	$0.023 (4.47)^a$	0.043 (5.53) <sup>a</sup>	$0.04 (6.84)^a$	0.025 (1.66) <sup>b</sup>
Evening Specific Alt.	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
VOT (TL/hr)	7.64	10.86	18.00	3.22	4.50
	4.91	2.57	10.80	3.22	4.30
	0.00	0.00	0.00	0.00	0.00
Scale Parameters (IVP)	0.00	$\theta_{d p} = 0.3(12.33)^{a}$	$0.00 \\ \theta_{t s} = 0.42(11.30)^{a}$	0.00 $\theta_{m s}=0.43(4.64)^{a}$	$\frac{0.00}{\theta_{d c}=0.63(2.63)^{a}}$
Scale Parameters (IVP)	0.00	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a \end{array}$	$\begin{array}{c} \theta_{t s} = 0.42(11.30)^{a} \\ \theta_{m p,s} = 0.38(2.2)^{a} \end{array}$		
Scale Parameters (IVP)	0.00	$\theta_{d p} = 0.3(12.33)^{a}$	$\theta_{t s}=0.42(11.30)^{a}$	$\theta_{m s}=0.43(4.64)^{a}$	$\theta_{d c} = 0.63(2.63)^a$
<u>Scale Parameters (IVP)</u>	0.00	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a \end{array}$	$\begin{array}{c} \theta_{t s} = 0.42(11.30)^{a} \\ \theta_{m p,s} = 0.38(2.2)^{a} \end{array}$	$\begin{array}{c} \theta_{m s} = 0.43(4.64)^{a} \\ \theta_{t c,s} = 0.15(3.9)^{a} \end{array}$	$\begin{array}{c} \theta_{d c} = 0.63(2.63)^a \\ \theta_{t s,c} = 0.31(2.7)^a \end{array}$
<u>Scale Parameters (IVP)</u>	0.00	$\begin{array}{l} \theta_{d p}=\!\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a \end{array}$	$\begin{array}{c} \theta_{t s} = 0.42(11.30)^{a} \\ \theta_{m p,s} = 0.38(2.2)^{a} \\ \theta_{m o,s} = 0.32(2.6)^{a} \end{array}$	$\begin{array}{l} \theta_{m s} = 0.43(4.64)^{a} \\ \theta_{t c,s} = 0.15(3.9)^{a} \\ \theta_{t pt,s} = 0.30(F) \end{array}$	$\begin{array}{l} \theta_{d c} = 0.63(2.63)^a \\ \theta_{t s,c} = 0.31(2.7)^a \\ \theta_{t l,c} = 0.28(3.4)^a \\ \theta_{t z,c} = 0.4(2.6)^a \end{array}$
<u>Scale Parameters (IVP)</u>	0.00	$\begin{split} \theta_{d p} = &0.3(12.33)^a \\ \theta_{m s,p} = &0.13(2.33)^a \\ \theta_{m l,p} = &0.08(3.22)^a \\ \theta_{m z,p} = &0.15(2.04)^a \\ \theta_{d p} = &0.95 \ (F) \end{split}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m e,s}{=}0.19(3.4)^{a} \\ \theta_{t l}{=}0.5(F) \end{array}$	$\begin{array}{c} \theta_{m s} = 0.43(4.64)^{a} \\ \theta_{t c,s} = 0.15(3.9)^{a} \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a}\\ \theta_{t s,c}{=}0.31(2.7)^{a}\\ \theta_{t l,c}{=}0.28(3.4)^{a}\\ \theta_{t z,c}=0.4(2.6)^{a}\\ \theta_{d pt}{=}0.98(1.6)^{b} \end{array}$
<u>Scale Parameters (IVP)</u>	0.00	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a \\ \theta_{m s,p}=0.13(2.33)^a \\ \theta_{m l,p}=0.08(3.22)^a \\ \theta_{m z,p}=0.15(2.04)^a \\ \\ \theta_{d o}=0.95 \ (F) \\ \theta_{m s,o}=0.53(3.70)^a \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m e,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \end{array}$	$\begin{array}{c} \theta_{m s}{=}0.43(4.64)^{a} \\ \theta_{t c,s}{=}0.15(3.9)^{a} \\ \theta_{t pt,s}{=}0.30(F) \\ \end{array}$ $\begin{array}{c} \theta_{m l}=\!0.48(4.1)^{a} \\ \theta_{t c,l}{=}0.18(3.9)^{a} \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a}\\ \theta_{t s,c}{=}0.31(2.7)^{a}\\ \theta_{t l,c}{=}0.28(3.4)^{a}\\ \theta_{t z,c}{=}0.4(2.6)^{a}\\ \hline\\ \theta_{d pt}{=}0.98(1.6)^{b}\\ \theta_{t s,pt}{=}0.77(4.6)^{a} \end{array}$
<u>Scale Parameters (IVP)</u>		$\begin{split} \theta_{d p} = &0.3(12.33)^a \\ \theta_{m s,p} = &0.13(2.33)^a \\ \theta_{m l,p} = &0.08(3.22)^a \\ \theta_{m z,p} = &0.15(2.04)^a \\ \theta_{d o} = &0.95 \ (F) \\ \theta_{m s,o} = &0.53(3.70)^a \\ \theta_{m l,o} = &0.32(4.90)^a \end{split}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m e,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \end{array}$	$\begin{array}{l} \theta_{m s}{=}0.43(4.64)^{a} \\ \theta_{t c,s}{=}0.15(3.9)^{a} \\ \theta_{t pt,s}{=}0.30(F) \\ \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \hline \\ \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \end{array}$
<u>Scale Parameters (IVP)</u>	0.00	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \end{array}\\ \begin{array}{l} \theta_{d o}=0.95~(F)\\ \theta_{m s,o}=0.53(3.70)^a \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m e,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \end{array}$	$\begin{array}{c} \theta_{m s}{=}0.43(4.64)^{a} \\ \theta_{t c,s}{=}0.15(3.9)^{a} \\ \theta_{t pt,s}{=}0.30(F) \\ \end{array}$ $\begin{array}{c} \theta_{m l}=\!0.48(4.1)^{a} \\ \theta_{t c,l}{=}0.18(3.9)^{a} \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a}\\ \theta_{t s,c}{=}0.31(2.7)^{a}\\ \theta_{t l,c}{=}0.28(3.4)^{a}\\ \theta_{t z,c}{=}0.4(2.6)^{a}\\ \hline\\ \theta_{d pt}{=}0.98(1.6)^{b}\\ \theta_{t s,pt}{=}0.77(4.6)^{a} \end{array}$
<u>Scale Parameters (IVP)</u>	0.00	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d o}=0.95~(F)\\ \theta_{m s,o}=0.53(3.70)^a\\ \theta_{m l,o}=0.32(4.90)^a\\ \theta_{m z,o}=0.50(3.80)^a \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m o,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}=0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \\ \theta_{m o,l}{=}0.36(2.5)^{a} \end{array}$	$\begin{array}{l} \theta_{m s}{=}0.43(4.64)^{a} \\ \theta_{t c,s}{=}0.15(3.9)^{a} \\ \theta_{t pt,s}{=}0.30(F) \\ \end{array}$ $\begin{array}{l} \theta_{m l}=\!0.48(4.1)^{a} \\ \theta_{t c,l}{=}0.18(3.9)^{a} \\ \theta_{t pt,l}{=}0.34(11.6)^{a} \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \hline \\ \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \end{array}$
<u>Scale Parameters (IVP)</u>		$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d o}=0.95~(F)\\ \theta_{m s,o}=0.53(3.70)^a\\ \theta_{m l,o}=0.32(4.90)^a\\ \theta_{m z,o}=0.50(3.80)^a\\ \theta_{d e}=1.00~(F) \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m o,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \\ \theta_{m o,l}{=}0.36(2.5)^{a} \\ \theta_{t z}{=}0.49(9.0)^{a} \end{array}$	$\begin{array}{l} \theta_{m s}{=}0.43(4.64)^{a}\\ \theta_{t c,s}{=}0.15(3.9)^{a}\\ \theta_{t pt,s}{=}0.30(F)\\ \end{array}\\ \\ \theta_{m l}=0.48(4.1)^{a}\\ \theta_{t c,l}{=}0.18(3.9)^{a}\\ \theta_{t pt,l}{=}0.34(11.6)^{a}\\ \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \hline \\ \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \end{array}$
<u>Scale Parameters (IVP)</u>		$\begin{split} & \theta_{d p} = 0.3(12.33)^a \\ & \theta_{m s,p} = 0.13(2.33)^a \\ & \theta_{m l,p} = 0.08(3.22)^a \\ & \theta_{m z,p} = 0.15(2.04)^a \\ & \theta_{d 0} = 0.95 \ (F) \\ & \theta_{m s,0} = 0.53(3.70)^a \\ & \theta_{m l,0} = 0.32(4.90)^a \\ & \theta_{m z,0} = 0.50(3.80)^a \\ & \theta_{d e} = 1.00 \ (F) \\ & \theta_{m s,e} = 0.30(3.30)^a \end{split}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a \\ \theta_{m p,s}{=}0.38(2.2)^a \\ \theta_{m o,s}{=}0.32(2.6)^a \\ \theta_{m o,s}{=}0.19(3.4)^a \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m e,l}{=}0.36(2.5)^a \\ \hline \\ \theta_{t z}{=}0.49(9.0)^a \\ \theta_{m p,z}{=}0.43(1.65)^b \end{array}$	$\begin{array}{l} \theta_{m s}{=}0.43(4.64)^{a} \\ \theta_{t c,s}{=}0.15(3.9)^{a} \\ \theta_{t pt,s}{=}0.30(F) \\ \end{array} \\ \\ \theta_{m l}=0.48(4.1)^{a} \\ \theta_{t c,l}{=}0.18(3.9)^{a} \\ \theta_{t pt,l}{=}0.34(11.6)^{a} \\ \\ \theta_{n z}{=}0.47(4.00)^{a} \\ \theta_{t c,z}{=}0.15(4.3)^{a} \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \hline \\ \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \end{array}$
<u>Scale Parameters (IVP)</u>		$\begin{split} & \theta_{d p} = 0.3(12.33)^a \\ & \theta_{m s,p} = 0.13(2.33)^a \\ & \theta_{m s,p} = 0.08(3.22)^a \\ & \theta_{m z,p} = 0.15(2.04)^a \\ & \theta_{d o} = 0.95 \ (F) \\ & \theta_{m s,o} = 0.53(3.70)^a \\ & \theta_{m l,o} = 0.32(4.90)^a \\ & \theta_{m z,o} = 0.50(3.80)^a \\ & \theta_{d e} = 1.00 \ (F) \\ & \theta_{m s,e} = 0.30(3.30)^a \\ & \theta_{m l,e} = 0.25(3.80)^a \end{split}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a \\ \theta_{m p,s}{=}0.38(2.2)^a \\ \theta_{m o,s}{=}0.32(2.6)^a \\ \theta_{m o,s}{=}0.19(3.4)^a \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m o,l}{=}0.36(2.5)^a \\ \hline \\ \theta_{t z}{=}0.49(9.0)^a \\ \theta_{m o,z}{=}0.27(2.9)^a \end{array}$	$\begin{array}{l} \theta_{m s}{=}0.43(4.64)^{a}\\ \theta_{t c,s}{=}0.15(3.9)^{a}\\ \theta_{t pt,s}{=}0.30(F)\\ \end{array}\\ \\ \theta_{m l}=0.48(4.1)^{a}\\ \theta_{t c,l}{=}0.18(3.9)^{a}\\ \theta_{t pt,l}{=}0.34(11.6)^{a}\\ \end{array}$	$\begin{array}{l} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \hline \\ \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \end{array}$
		$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m s,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d p}=0.95~(F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m l,p}=0.32(4.90)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \theta_{d e}=1.00~(F)\\ \theta_{m s,e}=0.30(3.30)^a\\ \theta_{m l,e}=0.25(3.80)^a\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m o,s}{=}0.19(3.4)^{a} \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \\ \theta_{m o,l}{=}0.36(2.5)^{a} \\ \theta_{t z}{=}0.49(9.0)^{a} \\ \theta_{m o,z}{=}0.27(2.9)^{a} \\ \theta_{m o,z}{=}0.29(2.7)^{a} \end{array}$	$\begin{array}{l} \theta_{m s}{=}0.43(4.64)^{a} \\ \theta_{t c,s}{=}0.15(3.9)^{a} \\ \theta_{t pl,s}{=}0.30(F) \\ \end{array} \\ \\ \theta_{m l}=0.48(4.1)^{a} \\ \theta_{t c,l}{=}0.18(3.9)^{a} \\ \theta_{t pl,l}{=}0.34(11.6)^{a} \\ \end{array} \\ \\ \\ \theta_{n z}{=}0.47(4.00)^{a} \\ \theta_{t c,z}{=}0.15(4.3)^{a} \\ \theta_{t pl,z}{=}0.43(8.8)^{a} \end{array}$	$\begin{array}{c} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \\ \theta_{t z,pt}{=}0.89(6.9)^{a} \end{array}$
# of Observations	529	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d p}=0.95~(F)\\ \theta_{m s,o}=0.53(3.70)^a\\ \theta_{m l,o}=0.32(4.90)^a\\ \theta_{m z,o}=0.50(3.80)^a\\ \theta_{d e}=1.00~(F)\\ \theta_{m s,e}=0.30(3.30)^a\\ \theta_{m l,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.29(3.40)^a\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m c,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \\ \theta_{m c,l}{=}0.36(2.5)^{a} \\ \hline \\ \theta_{t z}{=}0.49(9.0)^{a} \\ \hline \\ \theta_{m o,z}{=}0.27(2.9)^{a} \\ \theta_{m c,z}{=}0.29(2.7)^{a} \\ \hline \\ 529 \end{array}$	$\begin{array}{c} \theta_{m s} = 0.43(4.64)^{a} \\ \theta_{t c,s} = 0.15(3.9)^{a} \\ \theta_{t pl,s} = 0.30(F) \\ \hline \\ \theta_{m l} = 0.48(4.1)^{a} \\ \theta_{t c,l} = 0.18(3.9)^{a} \\ \theta_{t pl,l} = 0.34(11.6)^{a} \\ \hline \\ \theta_{n z} = 0.47(4.00)^{a} \\ \theta_{t c,z} = 0.15(4.3)^{a} \\ \theta_{t pl,z} = 0.43(8.8)^{a} \\ \hline \end{array}$	$\begin{array}{c} \theta_{d c}{=}0.63(2.63)^{a} \\ \theta_{t s,c}{=}0.31(2.7)^{a} \\ \theta_{t l,c}{=}0.28(3.4)^{a} \\ \theta_{t z,c}{=}0.4(2.6)^{a} \\ \hline \theta_{d pt}{=}0.98(1.6)^{b} \\ \theta_{t s,pt}{=}0.77(4.6)^{a} \\ \theta_{t l,pt}{=}0.74(F) \\ \theta_{t z,pt}{=}0.89(6.9)^{a} \\ \hline \end{array}$
# of Observations # of estimates	529 9	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \hline\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m l,p}=0.32(4.90)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \hline\\ \theta_{d e}=1.00\ (F)\\ \theta_{m s,e}=0.30(3.30)^a\\ \theta_{m z,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.29(3.40)^a\\ \hline\\ \theta_{m z,e}=1.9\\ \hline\end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m c,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \\ \theta_{m c,l}{=}0.36(2.5)^{a} \\ \hline \\ \theta_{t z}{=}0.49(9.0)^{a} \\ \hline \\ \theta_{m o,z}{=}0.27(2.9)^{a} \\ \theta_{m c,z}{=}0.29(2.7)^{a} \\ 529 \\ 20 \end{array}$	$\begin{array}{c} \theta_{m s} = 0.43(4.64)^{a} \\ \theta_{t c,s} = 0.15(3.9)^{a} \\ \theta_{t pl,s} = 0.30(F) \\ \hline \\ \theta_{m l} = 0.48(4.1)^{a} \\ \theta_{t c,l} = 0.18(3.9)^{a} \\ \theta_{t c,l} = 0.34(11.6)^{a} \\ \hline \\ \theta_{n z} = 0.47(4.00)^{a} \\ \theta_{t c,z} = 0.15(4.3)^{a} \\ \theta_{t pl,z} = 0.43(8.8)^{a} \\ \hline \\ \end{array}$	$\begin{array}{c} \hline \theta_{d c} = 0.63(2.63)^a \\ \theta_{t s,c} = 0.31(2.7)^a \\ \theta_{t l,c} = 0.28(3.4)^a \\ \theta_{t z,c} = 0.4(2.6)^a \\ \hline \theta_{d pt} = 0.98(1.6)^b \\ \theta_{t s,pt} = 0.77(4.6)^a \\ \theta_{t l,pt} = 0.74(F) \\ \theta_{t z,pt} = 0.89(6.9)^a \\ \hline \end{array}$
# of Observations # of estimates LL(0)	529 9 NA	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m l,p}=0.32(4.90)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \theta_{d z}=1.00\ (F)\\ \theta_{m s,z}=0.30(3.30)^a\\ \theta_{m z,z}=0.25(3.80)^a\\ \theta_{m z,z}=0.29(3.40)^a\\ 529\\ 19\\ -1743.50\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a \\ \theta_{m p,s}{=}0.38(2.2)^a \\ \theta_{m o,s}{=}0.32(2.6)^a \\ \theta_{m c,s}{=}0.19(3.4)^a \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m c,l}{=}0.36(2.5)^a \\ \hline \\ \theta_{t z}{=}0.49(9.0)^a \\ \hline \\ \theta_{m c,z}{=}0.27(2.9)^a \\ \theta_{m c,z}{=}0.29(2.7)^a \\ \hline \\ 529 \\ 20 \\ {-}1743.50 \\ \end{array}$	$\begin{array}{c} \theta_{m s} \!\!=\!\! 0.43(4.64)^a \\ \theta_{t c,s} \!\!=\!\! 0.15(3.9)^a \\ \theta_{t pl,s} \!\!=\!\! 0.30(F) \\ \hline \\ \theta_{m l} \!\!=\!\! 0.48(4.1)^a \\ \theta_{t c,l} \!\!=\!\! 0.18(3.9)^a \\ \theta_{t pl,l} \!\!=\!\! 0.34(11.6)^a \\ \hline \\ \theta_{n z} \!\!=\!\! 0.47(4.00)^a \\ \theta_{t c,z} \!\!=\!\! 0.15(4.3)^a \\ \theta_{t pl,z} \!\!=\!\! 0.43(8.8)^a \\ \hline \\ 529 \\ 17 \\ -1815.30 \end{array}$	$\begin{array}{c} \hline \theta_{d c}{=}0.63(2.63)^a \\ \theta_{t s,c}{=}0.31(2.7)^a \\ \theta_{t l,c}{=}0.28(3.4)^a \\ \theta_{t z,c}{=}0.4(2.6)^a \\ \hline \theta_{d pt}{=}0.98(1.6)^b \\ \theta_{t s,pt}{=}0.77(4.6)^a \\ \theta_{t l,pt}{=}0.74(F) \\ \theta_{t z,pt}{=}0.89(6.9)^a \\ \hline \\ 529 \\ 16 \\ -1815.30 \end{array}$
# of Observations # of estimates	529 9	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \hline\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m l,p}=0.32(4.90)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \hline\\ \theta_{d e}=1.00\ (F)\\ \theta_{m s,e}=0.30(3.30)^a\\ \theta_{m z,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.29(3.40)^a\\ \hline\\ \theta_{m z,e}=1.9\\ \hline\end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^{a} \\ \theta_{m p,s}{=}0.38(2.2)^{a} \\ \theta_{m o,s}{=}0.32(2.6)^{a} \\ \theta_{m c,s}{=}0.19(3.4)^{a} \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^{a} \\ \theta_{m o,l}{=}0.22(3.4)^{a} \\ \theta_{m c,l}{=}0.36(2.5)^{a} \\ \hline \\ \theta_{t z}{=}0.49(9.0)^{a} \\ \hline \\ \theta_{m o,z}{=}0.27(2.9)^{a} \\ \theta_{m c,z}{=}0.29(2.7)^{a} \\ 529 \\ 20 \end{array}$	$\begin{array}{c} \theta_{m s} = 0.43(4.64)^{a} \\ \theta_{t c,s} = 0.15(3.9)^{a} \\ \theta_{t pl,s} = 0.30(F) \\ \hline \\ \theta_{m l} = 0.48(4.1)^{a} \\ \theta_{t c,l} = 0.18(3.9)^{a} \\ \theta_{t c,l} = 0.34(11.6)^{a} \\ \hline \\ \theta_{n z} = 0.47(4.00)^{a} \\ \theta_{t c,z} = 0.15(4.3)^{a} \\ \theta_{t pl,z} = 0.43(8.8)^{a} \\ \hline \\ \end{array}$	$\begin{array}{c} \hline \theta_{d c} = 0.63(2.63)^a \\ \theta_{t s,c} = 0.31(2.7)^a \\ \theta_{t l,c} = 0.28(3.4)^a \\ \theta_{t z,c} = 0.4(2.6)^a \\ \hline \theta_{d pt} = 0.98(1.6)^b \\ \theta_{t s,pt} = 0.77(4.6)^a \\ \theta_{t l,pt} = 0.74(F) \\ \theta_{t z,pt} = 0.89(6.9)^a \\ \hline \end{array}$
# of Observations # of estimates LL(0)	529 9 NA	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m l,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m l,p}=0.32(4.90)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \theta_{d z}=1.00\ (F)\\ \theta_{m s,z}=0.25(3.80)^a\\ \theta_{m z,z}=0.29(3.40)^a\\ 529\\ 19\\ -1743.50\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a \\ \theta_{m p,s}{=}0.38(2.2)^a \\ \theta_{m o,s}{=}0.32(2.6)^a \\ \theta_{m c,s}{=}0.19(3.4)^a \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m c,l}{=}0.36(2.5)^a \\ \hline \\ \theta_{t z}{=}0.49(9.0)^a \\ \hline \\ \theta_{m c,z}{=}0.27(2.9)^a \\ \theta_{m c,z}{=}0.29(2.7)^a \\ \hline \\ 529 \\ 20 \\ {-}1743.50 \\ \end{array}$	$\begin{array}{c} \theta_{m s} \!\!=\!\! 0.43(4.64)^a \\ \theta_{t c,s} \!\!=\!\! 0.15(3.9)^a \\ \theta_{t pl,s} \!\!=\!\! 0.30(F) \\ \hline \\ \theta_{m l} \!\!=\!\! 0.48(4.1)^a \\ \theta_{t c,l} \!\!=\!\! 0.18(3.9)^a \\ \theta_{t pl,l} \!\!=\!\! 0.34(11.6)^a \\ \hline \\ \theta_{n z} \!\!=\!\! 0.47(4.00)^a \\ \theta_{t c,z} \!\!=\!\! 0.15(4.3)^a \\ \theta_{t pl,z} \!\!=\!\! 0.43(8.8)^a \\ \hline \\ 529 \\ 17 \\ -1815.30 \end{array}$	$\begin{array}{c} \hline \theta_{d c}{=}0.63(2.63)^a \\ \theta_{t s,c}{=}0.31(2.7)^a \\ \theta_{t l,c}{=}0.28(3.4)^a \\ \theta_{t z,c}{=}0.4(2.6)^a \\ \hline \theta_{d pt}{=}0.98(1.6)^b \\ \theta_{t s,pt}{=}0.77(4.6)^a \\ \theta_{t l,pt}{=}0.74(F) \\ \theta_{t z,pt}{=}0.89(6.9)^a \\ \hline \\ 529 \\ 16 \\ -1815.30 \end{array}$
# of Observations # of estimates LL(0) LL(β) LL(C)	529 9 NA -1540.02	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m s,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \hline\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m l,p}=0.32(4.90)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \hline\\ \theta_{d e}=1.00\ (F)\\ \hline\\ \theta_{m s,e}=0.30(3.30)^a\\ \theta_{m z,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.29(3.40)^a\\ \hline\\ 529\\ 19\\ -1743.50\\ -1512.57\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a\\ \theta_{m p,s}{=}0.38(2.2)^a\\ \theta_{m o,s}{=}0.32(2.6)^a\\ \theta_{m o,s}{=}0.19(3.4)^a\\ \hline\\ \theta_{t l}{=}0.5(F)\\ \theta_{m o,l}{=}0.19(3.5)^a\\ \theta_{m o,l}{=}0.22(3.4)^a\\ \theta_{m o,l}{=}0.36(2.5)^a\\ \hline\\ \theta_{t z}{=}0.49(9.0)^a\\ \theta_{m o,z}{=}0.27(2.9)^a\\ \theta_{m o,z}{=}0.27(2.9)^a\\ \theta_{m o,z}{=}0.29(2.7)^a\\ 529\\ 20\\ {-}1743.50\\ {-}1521.04\\ \end{array}$	$\begin{array}{c} \theta_{m s} \!\!=\!\! 0.43(4.64)^a \\ \theta_{t c,s} \!\!=\!\! 0.15(3.9)^a \\ \theta_{t pl,s} \!\!=\!\! 0.30(F) \\ \hline \\ \theta_{m l} \!\!=\!\! 0.48(4.1)^a \\ \theta_{t c,l} \!\!=\!\! 0.18(3.9)^a \\ \theta_{t pl,l} \!\!=\!\! 0.34(11.6)^a \\ \hline \\ \theta_{n z} \!\!=\!\! 0.47(4.00)^a \\ \theta_{t c,z} \!\!=\!\! 0.15(4.3)^a \\ \theta_{t pl,z} \!\!=\!\! 0.43(8.8)^a \\ \hline \\ 529 \\ 17 \\ -1815.30 \\ -1517.78 \end{array}$	$\begin{array}{c} \hline \theta_{d c}{=}0.63(2.63)^a \\ \theta_{t s,c}{=}0.31(2.7)^a \\ \theta_{t l,c}{=}0.28(3.4)^a \\ \theta_{t l,c}{=}0.28(3.4)^a \\ \theta_{d pt}{=}0.98(1.6)^b \\ \hline \theta_{t s,pt}{=}0.77(4.6)^a \\ \theta_{t l,pt}{=}0.74(F) \\ \theta_{t l,pt}{=}0.89(6.9)^a \\ \hline \\ 529 \\ 16 \\ -1815.30 \\ -1532.54 \end{array}$
# of Observations # of estimates LL(0) LL(β) LL(C) -2LL[βvs.C] (χ <sup>2</sup> =14.1)	529 9 NA -1540.02 -1666.90	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m s,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,p}=0.53(3.70)^a\\ \theta_{m z,p}=0.50(3.80)^a\\ \theta_{d z}=1.00\ (F)\\ \theta_{m s,z}=0.30(3.30)^a\\ \theta_{m z,z}=0.29(3.80)^a\\ \theta_{m z,z}=0.29(3.40)^a\\ 529\\ 19\\ -1743.50\\ -1512.57\\ -1655.13\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a\\ \theta_{m p,s}{=}0.38(2.2)^a\\ \theta_{m o,s}{=}0.32(2.6)^a\\ \theta_{m o,s}{=}0.19(3.4)^a\\ \hline\\ \theta_{t l}{=}0.5(F)\\ \theta_{m o,l}{=}0.19(3.5)^a\\ \theta_{m o,l}{=}0.22(3.4)^a\\ \theta_{m o,l}{=}0.36(2.5)^a\\ \hline\\ \theta_{t z}{=}0.49(9.0)^a\\ \theta_{m o,z}{=}0.27(2.9)^a\\ \theta_{m o,z}{=}0.27(2.9)^a\\ \theta_{m o,z}{=}0.29(2.7)^a\\ 529\\ 20\\ {-}1743.50\\ {-}1521.04\\ {-}1655.53\\ \end{array}$	$\begin{array}{c} \theta_{m s} \!\!=\!\! 0.43(4.64)^a \\ \theta_{t c,s} \!\!=\!\! 0.15(3.9)^a \\ \theta_{t pl,s} \!\!=\!\! 0.30(F) \\ \hline \\ \theta_{m l} \!\!=\!\! 0.48(4.1)^a \\ \theta_{t c,l} \!\!=\!\! 0.18(3.9)^a \\ \theta_{t pl,l} \!\!=\!\! 0.34(11.6)^a \\ \hline \\ \theta_{n z} \!\!=\!\! 0.47(4.00)^a \\ \theta_{t c,z} \!\!=\!\! 0.15(4.3)^a \\ \theta_{t pl,z} \!\!=\!\! 0.43(8.8)^a \\ \hline \\ 529 \\ 17 \\ \!\!-\! 1815.30 \\ \!\!\!-\! 1517.78 \\ \!\!-\! 1655.90 \end{array}$	$\begin{array}{c} \hline \theta_{d c}{=}0.63(2.63)^a \\ \theta_{t s,c}{=}0.31(2.7)^a \\ \theta_{t l,c}{=}0.28(3.4)^a \\ \theta_{t l,c}{=}0.28(3.4)^a \\ \theta_{d pt}{=}0.98(1.6)^b \\ \hline \theta_{d pt}{=}0.98(1.6)^b \\ \theta_{t s,pt}{=}0.77(4.6)^a \\ \theta_{t l,pt}{=}0.74(F) \\ \theta_{t l,pt}{=}0.89(6.9)^a \\ \hline \\ 529 \\ 16 \\ -1815.30 \\ -1532.54 \\ -1621.87 \end{array}$
# of Observations # of estimates LL(0) LL(β) LL(C) -2LL[βvs.C] (χ <sup>2</sup> =14.1) ρ <sup>2</sup> (βvs.C)	529 9 NA -1540.02 -1666.90 253.76 0.076	$\begin{array}{l} \theta_{d p}=0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m s,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \theta_{d p}=0.95\ (F)\\ \theta_{m s,o}=0.53(3.70)^a\\ \theta_{m l,o}=0.32(4.90)^a\\ \theta_{m z,o}=0.50(3.80)^a\\ \theta_{m z,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.29(3.40)^a\\ 529\\ 19\\ -1743.50\\ -1512.57\\ -1655.13\\ 285.12\\ 0.086\end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a \\ \theta_{m p,s}{=}0.38(2.2)^a \\ \theta_{m p,s}{=}0.32(2.6)^a \\ \theta_{m e,s}{=}0.19(3.4)^a \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m e,l}{=}0.36(2.5)^a \\ \theta_{m p,z}{=}0.43(1.65)^b \\ \theta_{m o,z}{=}0.27(2.9)^a \\ \theta_{m e,z}{=}0.29(2.7)^a \\ 529 \\ 20 \\ -1743.50 \\ -1521.04 \\ -1655.53 \\ 268.98 \\ 0.081 \\ \end{array}$	$\begin{array}{c} \theta_{m s}{=}0.43(4.64)^a \\ \theta_{t c,s}{=}0.15(3.9)^a \\ \theta_{t pt,s}{=}0.30(F) \\ \end{array} \\ \\ \theta_{m t} {=}0.48(4.1)^a \\ \theta_{t c,t}{=}0.18(3.9)^a \\ \theta_{t pt,t}{=}0.34(11.6)^a \\ \end{array} \\ \\ \\ \theta_{n z}{=}0.47(4.00)^a \\ \theta_{t c,z}{=}0.15(4.3)^a \\ \theta_{t pt,z}{=}0.43(8.8)^a \\ \end{array} \\ \\ \\ \hline \\ 529 \\ 17 \\ -1815.30 \\ -1517.78 \\ -1655.90 \\ 276.24 \\ 0.083 \\ \end{array}$	$\begin{array}{c} \hline \theta_{d c} = 0.63(2.63)^a \\ \theta_{t s,c} = 0.31(2.7)^a \\ \theta_{t s,c} = 0.28(3.4)^a \\ \theta_{t c,c} = 0.4(2.6)^a \\ \hline \theta_{d pt} = 0.98(1.6)^b \\ \hline \theta_{t s,pt} = 0.77(4.6)^a \\ \theta_{t t,pt} = 0.74(F) \\ \theta_{t c,pt} = 0.89(6.9)^a \\ \hline \end{array}$
# of Observations # of estimates LL(0) LL(β) LL(C) -2LL[βvs.C] (χ <sup>2</sup> =14.1)	529 9 NA -1540.02 -1666.90 253.76	$\begin{array}{l} \theta_{d p}=\!0.3(12.33)^a\\ \theta_{m s,p}=0.13(2.33)^a\\ \theta_{m s,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.08(3.22)^a\\ \theta_{m z,p}=0.15(2.04)^a\\ \hline\\ \theta_{d o}=0.95\ (F)\\ \theta_{m s,o}=0.53(3.70)^a\\ \theta_{m z,o}=0.32(4.90)^a\\ \theta_{m z,o}=0.30(3.80)^a\\ \hline\\ \theta_{d e}=1.00\ (F)\\ \theta_{m s,e}=0.25(3.80)^a\\ \theta_{m z,e}=0.29(3.40)^a\\ \hline\\ \sigma_{12}=0.29(3.40)^a\\ 19\\ -1743.50\\ -1512.57\\ -1655.13\\ 285.12\\ \end{array}$	$\begin{array}{c} \theta_{t s}{=}0.42(11.30)^a \\ \theta_{m p,s}{=}0.38(2.2)^a \\ \theta_{m o,s}{=}0.32(2.6)^a \\ \theta_{m e,s}{=}0.19(3.4)^a \\ \hline \\ \theta_{t l}{=}0.5(F) \\ \theta_{m p,l}{=}0.19(3.5)^a \\ \theta_{m o,l}{=}0.22(3.4)^a \\ \theta_{m o,l}{=}0.36(2.5)^a \\ \theta_{m o,z}{=}0.43(1.65)^b \\ \theta_{m o,z}{=}0.27(2.9)^a \\ \theta_{m e,z}{=}0.29(2.7)^a \\ 529 \\ 20 \\ -1743.50 \\ -1521.04 \\ -1655.53 \\ 268.98 \\ \end{array}$	$\begin{array}{c} \theta_{m s}{=}0.43(4.64)^a \\ \theta_{t c,s}{=}0.15(3.9)^a \\ \theta_{t pt,s}{=}0.30(F) \\ \hline \\ \theta_{m t}{=}0.48(4.1)^a \\ \theta_{t c,t}{=}0.18(3.9)^a \\ \theta_{t c,t}{=}0.18(3.9)^a \\ \theta_{t pt,t}{=}0.34(11.6)^a \\ \hline \\ \theta_{n z}{=}0.47(4.00)^a \\ \theta_{t c,z}{=}0.15(4.3)^a \\ \theta_{t pt,z}{=}0.43(8.8)^a \\ \hline \\ 529 \\ 17 \\ {-}1815.30 \\ {-}1517.78 \\ {-}1655.90 \\ 276.24 \end{array}$	$\begin{array}{c} \hline \theta_{d c} = 0.63(2.63)^a \\ \theta_{t s,c} = 0.31(2.7)^a \\ \theta_{t s,c} = 0.28(3.4)^a \\ \theta_{t z,c} = 0.4(2.6)^a \\ \hline \theta_{d pt} = 0.98(1.6)^b \\ \theta_{t s,pt} = 0.77(4.6)^a \\ \theta_{t t,pt} = 0.74(F) \\ \theta_{t z,pt} = 0.89(6.9)^a \\ \hline \\ 529 \\ 16 \\ -1815.30 \\ -1532.54 \\ -1621.87 \\ 178.66 \\ \end{array}$

Table 2.5 : The coefficient estimates for 3-levels NL models.

F=Fixed Parameter, NA= Not Applicable, <sup>a</sup> Significant at 95% level, <sup>b</sup> Significant at 90% level, t-statistics in parentheses

The productive models have different nesting structure where; NS-1 has the arrangement of departure times, destinations and transportation modes at the upper, the mid, the lower level respectively. In NS-2, destinations are settled at top level, departure times follow it at the mid-level and transportation modes are allocated at

lower. The rest two structures (NS-3 and NS-4) consider the potential similarity among bus and tramway alternatives at specific levels where; NS-3 considers destinations at top, transportation modes with two specific branches at mid-level (private car and public transportations) and departure times at the lower level. NS-4, however, treats transportation modes at upper level with two branches (private car and public transportations), destinations and departure times follow at mid and lower levels respectively. According to estimation results, the following conclusions can be figured out:

- In terms of overall goodness of fit, the 4 proposed models achieve acceptable values where log likelihood ratios exceed the critical  $\chi^2$  at 5% level of significance
- Regarding scale parameters, in the 4 models, all values are in between the acceptable ranges where; by normalizing scale parameters at top levels, the mid-level scale parameters (e.g.  $\theta_{d|p}$ ,  $\theta_{d|o}$  and  $\theta_{d|e}$  in NS-1) are less than or equal to one and more than zero. However, the lower level scale parameters (e.g.  $\theta_{m|s,p}$   $\theta_{m|l,p}$  and  $\theta_{m|z,p}$  in NS-1) are less than or equal to the parameters of the mid-level and more than zero (e.g.  $1.00 > \theta_{d|t} > \theta_{m|d,t} > 0$ ).
- The signs of departure time specific estimates of travel time are consistent for all models (negative). The magnitudes, however, are more coherent in NS-1 and NS-2 than NS-3 and NS-4. In NS-1 and NS-2, the magnitudes of travel time estimates reflect that while performing shopping and entertainment trips, individuals of Eskisehir perceive more importance for total travel time in peak periods than off-peak periods, nevertheless, NS-3 and NS-4 suggest equal perceptions for both times.
- The negative signs of the generic total cost parameters in all models indicate intuitively the inclination of decreasing utilities of shopping and entertainment trips as travel cost increases.
- The mode specific estimates of car ownership associated with private car have positive sings (as expected) in all of 4 models which lead to the fact that the availability of private car increase the likelihood of using private car over public transportation to shopping and entertainment destinations.
- The income parameters (specific to destination) turn to be insignificant in all models except for NS-4 where the Local Bazaar specific income parameter is

significant at 10%, however, the positive sign related to it leads to illogic interpretation where it suggests that individuals with higher monthly income are more likely prefer doing shopping in Local Bazaar than shopping malls.

- Specific to private car mode, being a student represents a significant variable with negative parameter for all models. Obviously, while applying shopping and entertainment trips, being a student increase the probability of using public transportation modes over private car.
- The estimates of Age variable are significantly different than zero and have positive signs in all models. Specific to departure time, getting older decreases the probability of performing shopping and entertainment trips at peak periods and evening as well.
- Reviewing the value of time "VOT" leads to conclude that, models of NS-1 and NS-2 have more reliable values than models of NS-3 and NS-4 where individuals generally perceive more willingness to pay at peak periods over at off-peak periods rather than similar perceptions at both periods. Furthermore, the magnitudes of VOT in NS-1 (10.86 TL/hr at peak, 2.57 at off-peak and 0 at evening) may be more reasonable than their magnitudes in NS-2 (18.00 TL/hr at peak, 10.80 at off-peak and 0 at evening) where the magnitude of VOT at peak in the former is closer to average hourly wage rate which equals about 12 TL/hr (average monthly income is 2160 TL, 22 work days and 8 hours working per day).
- The 4 proposed 3-level NL models are developed significantly over the less advanced MNL where the values of log likelihood ratio of 3-level relative to the MNL exceed the critical  $\chi^2$  at 5% level of significance and different degree of freedoms.
- Maximum of maximum log likelihood value is associated with NS-1 (-1512.57) with highest log likelihood ratio relative to the MNL model (54.90). That may lead to conclude that for shopping and entertainment trips, individuals in Eskisehir city are more likely deciding at first on departure time which follows by deciding on destination which follows by transportation modes.
- From another hand, the value of maximum log likelihood of model NS-2 (-1521.78) is slightly lesser than the maximum one of NS-1 with acceptable signs

and magnitudes for estimates and VOT. That sheds the light on a considerable portion of sample that may consider the proposed nesting structure NS-2 as a decision role while travelling to shopping and entertainment trips (destination, then time of day, then transportation mode). The existence of two different nesting structures with close overall goodness of fit can be interpreted as a portion of heterogeneity in the sample (as presenter to the overall population) which can be considered with more advanced choice models, however, this approach is out of the scope of this research.

- The models NS-3 and NS-4 are arguable to be accepted even if they have a considerable LL value with significant LL ratio relatively to the less advanced MNL model. The main reason is the equal values associated with the departure time specific travel time estimates which lead to equal VOTs for both peak and off-peak periods as illustrated previously. Moreover, the positive sign of income variable parameter for Local Bazaar in NS-4 is against intuition.
- As a conclusion, it is proper to consider NS-1 as the best 3-level NL model which represents the correlation among time of day, destination and transportation mode choices while performing shopping and entertainment trips for individuals in Eskisehir city.
- Overall, the 3-level NL model achieves the connectivity among different travel choices that are common in the same trip (e.g. time of day, destination and transportation mode) rather than treating them separately as 4-step model does. Obviously, in the light of the estimation results, the relative values of scale parameters support that decision makers are more likely decide on different travel choices jointly rather than separately. Therefore, neglecting such dependency (correlation) may lead to insufficient and inconsistent models. That can be clearly demonstrated through comparing the results of the proposed model with other studies which did not consider correlation between different travel dimensions. For example, the model proposed by Bowman and Ben-Akiva (2001) has connected departure times from one side with the combinations of destinations and travel modes from the other without accounting for associated correlations. The estimation results of the model's prototype that was introduced for Boston are found to have some faults. For instance, unrealistic estimates for VOT have been obtained. Another example is the study that was attained by Elmorssy and Tezcan (2019). In that research,

they have introduced the correlation between departure time, destination and travel mode through 2-level NL rather than 3-level. Such a representation has resulted in restricted correlation patterns and lesser detailed inter-dependency. According to the estimation results, unlike to ours, their model was very slightly developed over MNL model.

• Finally, our proposed model has succeeded in representing disaggregate behaviour for limited number of travel dimensions (e.g. 3 times, 3 destinations and 3 modes) which makes it reliable and more accurate for small-scale planning issues. However, it has the capability to analyse large-scale planning horizons by calibrating it with aggregate-data.

## 2.9 Conclusions

This research aims to represent departure time, destination and travel mode choices under a unified disaggregate model that can consider for the potential inter-correlation among them. In order to attain that, discrete 3-level NL model is suggested to be used. Through it, different potential correlation patterns were constructed via the associated nesting structures. The proposed model provided a reliable and applicable alternative representation that can substitute the first 3-steps in the traditional 4-step model. The formulated models have been examined on disaggregate shopping and entertainment travels' data that are obtained in 2015 from Eskisehir city's household survey, Turkey.

The estimation results lead to significant conclusions which may be summarized in the following points:

- Opposite to 4-step model, the proposed model shows adequate flexibility in accounting for attributes of alternatives and characteristics of decision makers as well which results in a more consistent behavioural travel demand representation.
- Moreover, our proposed approach provides behavioural-based simulation instrument that can be used to test various hypothetical situations to precisely predict future travel demand preferences under temporal, spatial, socioeconomic and demographic changes.
- Finally, the proposed model may be considered as a significant milestone toward obtaining a consistent, efficient and integrated full-scale behavioural-model that can lie in all travel demand dimensions.



## 3. ORDERED GENERALIZED EXTREME VALUE MODEL AS A TOOL FOR DEMAND MODELLING OF DISCRETIONARY TRIPS <sup>2</sup>

#### **3.1 Abstract**

Despite four-step model is the most common method in transportation demand modelling, it is exposed to a considerable criticism in terms of representing actual choice behaviours of travellers. For example, the four steps are presented in a fixed sequence and independently from each other. Such assumption may be correct in case of obligatory trips (e.g. work trips) where travellers' behaviour has usually no effect on trip generation or trip distribution stages. However, in discretionary trips, they may simultaneously decide on various trip dimensions. This paper tries to overcome the limitations of traditional four-step model associated with discretionary trips by using a joint discrete choice modelling approach that represents destination, departure time and travel mode choices under a unified framework. The proposed model to be used is the Ordered Generalized Extreme Value model where potential spatial correlation among discretionary destinations can be considered as well. The research methodology has been tested by using shopping and entertainment trips data of Eskisehir city in Turkey. The proposed framework seemed to be more effective and offered an accurate alternative to the first three stages of the traditional four-step model in a setting where a limited number of discretionary destinations exists.

#### **3.2 Introduction**

Since four-step model was developed in the 1960s, the sequence of the steps has remained unchanged (Ortuzar and Willumsen, 2011). For instance, it is assumed arbitrarily that trip distribution (destination choice) comes in the second step and independently followed by travel mode choice. However, that sequence may be violated in discretionary trips (i.e. non-obligatory trips) where travellers may

<sup>&</sup>lt;sup>2</sup> This chapter is based on the paper "Ordered Generalized Extreme Value Model as a Tool for Demand Modelling of Discretionary Trips", Promet – Traffic & Transportation, Vol. 32, 2020, No. 2, 193-205

simultaneously decide on destination, travel mode and other considered travel dimensions such as departure time (Marshall, 2018).

Considering trip distribution stage, over years, there is a serious competition between destination choice models from one side and other conventional methods (e.g. growth factor methods, gravity models, etc.) from another (Ortuzar and Willumsen, 2011). Despite destination choice models show better performance in terms of goodness of fit and predictability, the two competing approaches are similar in the distribution theory. That is, all of them ignore the potential interaction between destination choice and other travel dimensions that may exist within the same choice situation. For example, for discretionary trips and in case of a congested network, most destination distribution models assume compensations between closer destinations depending on the relative origin-destination impedance function (e.g.travel time). However, this assumption ignores the fact that individuals may shift their departure time or change the travel mode to travel to their desired destination. On the other hand, most researches that considered the interaction between destination choice and other simultaneous choices did ignore the potential spatial correlation between different destinations (Hassan et al, 2017).

As there is a gap in the literature about representing a unified model that connects destination choice with other travel dimensions' choices, this research contributes filling this gap through applying the Ordered Generalized Extreme Value (OGEV) model. Such a model will account for spatial correlation among different discretionary destinations along with considering simultaneous choices of two of the most significant travel dimensions which are departure time and travelling mode. The proposed approach can be seen as a more accurate and efficient alternative for the first three steps of the traditional four-step model in forecasting and planning issues especially when the scale is small or medium sized (e.g. small and medium sized cities).

#### **3.3 Literature Review**

Choice modelling approach is usually used for only modal split stage in most of the traditional four-step models with little or no deployment in other stages (Hassan et al, 2017). For instance, in most of applications, aggregate gravity models are used extensively in trip distribution stage independently from travel mode choice stage.

However, recently, discrete choice models have been introduced as an alternative to conventional gravity models to represent destination choice along with other travel choices (e.g. departure time and travel mode choices) (Molloy, 2016). Such a representation has served different modelling approaches (e.g. trip-based and activity-based models) either as a part of four-step model or as independent models (Rasouli and Timmermans,2013; Yoon et al, 2012; Scott and He, 2012; Auld and Mohammadian, 2011; Pozsgay and Bhat, 2001; Bhat et al, 1998; Miller and Kelly, 1983). Through the following lines, we shed the light on some of the related studies that used choice modelling as an alternative to traditional four-step models for demand modelling.

With regard to using choice modelling for destination choice (i.e. trip distribution), methodology and applications of models have been defined firstly in 1977 by Ben-Akiva (Ben-Akiva, 1977). However, Daly (1982) has analysed the attractiveness of destinations in such models. This approach was followed by researches that adopted different discrete choice models for different trip purposes. For example, Pozsgay and Bhat (2001) have developed a home-based entertainment destination choice model that considered a lot of trip attributes and socio-demographic characteristics of individuals as variables. They concluded that adjacent recreational zones are more likely preferred than isolated ones. Similarly, in Switzerland, Simma et al (2001) have proposed a leisure destination choice model that accounted for some destination attractiveness variables (e.g. number of swimming pools). As a result, origin-destination distance has found to be the most important factor that affects individuals' leisure destination choices. Mishra et al (2013) have introduced a Multinomial Logit (MNL) destination choice model for Maryland. Through comparing with traditional gravity model, destination choice model has been found better for state-wide travel demand modelling. Another research that recently represented individuals' behaviour while choosing among entertainment destinations is the one attained by Hassan et al (2017). They studied the choice of destination according to the type of recreational activity (e.g. dine and drink, gym, park, etc.) in Victoria, Australia. The average behaviour of all activities has been introduced through developing a combined fuzzy MNL model that consists of all activities together. The study concluded that the most important factors that affect individuals' destination choices are travel time, number of origin destination trips and level of urbanization. Additionally, individuals' characteristics

such as age, income and employment status have some significant effects on their destination choices.

Another important travel dimension that is considered in our analysis along with destination choice is the departure time choice. The importance of modelling departure time as a part of the trip decision arises from the need to better understand the interrelationship between congestion and the distribution of trips over different times of day. In the context of time representation approaches, while some studies have developed discrete choice-based departure time models (Elmorssy and Tezcan, 2019; Bates et al, 2001; Bhat, 1998), others have adopted the continuous representation of time through different modelling techniques such as MNL, Nested Logit (NL), etc. (Pinjari and Bhat, 2010; Bhat, 2008; Bhat, 2005). Moreover, under the umbrella of activity-based modelling, some scholars have examined the effects of time of day choices on the daily activity patterns (Pinjari and Bhat, 2010; Bhat, 2005; Yagi and Mohammadian, 2010). Moreover, in some other studies the effects of departure time were examined from a tour-based modelling viewpoint (Outwater et al, 2015; Shiftan, 1998).

Considering the approaches that jointly represented destination choice with other travel dimensions' choices, Bowman and Ben-Akiva (2001) have introduced an integrated destination choice activity model system that can generate time and mode specific trip matrices. By using a multi-level NL model, they have assigned one branch for departure time choices and another branch for combinations of travel mode and destination choice. However, each level is estimated separately rather than simultaneously with other levels. Likewise, Outwater et al (2015); Mishra et al (2011); Newman and Bernardin (2010) have developed unified destination-mode-choice models that represent the influence of mode choice on destination choices through imposing the log-sum parameter of mode choice as a parameter in destination choice.

Worth mentioning, a common significant feature in most of above pointed researches is that they do not consider for the potential correlation among destinations. Instead, they treat them as mutually exclusive alternatives with identical independent distribution (IID) for their error terms. However, there are many sources of potential correlation between destination alternatives. For example, a spatial correlation between adjacent zones may exist due to the arbitrary definition of their boundaries (Hassan et al, 2017). Such a definition is usually unknown to most of travellers which leads them to construct their own boundaries in their minds depending on unknown factors.

An approach that can effectively connect destination choice with departure time and travel mode and consider for various potential spatial correlation between destinations is the OGEV model (Small, 1987). OGEV allows destinations that are located (ordered) in a specific pattern to have common unobserved errors. This paper argues that, an efficient joint model for destination, departure time, and travel mode choices can be attained through using the OGEV model.

#### **3.4 Proposed Framework**

Through OGEV, the spatial effect of discretionary destinations on both departure time and travel mode choice can be more accurately represented. Indeed, it provides a more accurate representation for the ordered nature among neighbouring destinations. The OGEV model was proposed by Small (1987) under the context of departure time choice modelling. It is considered as a special case of Cross Nested Logit (CNL) model, in which alternatives within a specific nest may occur in other nests if there are other potential unobserved similarities. However, in OGEV, similarities between alternatives are controlled by the relative closeness among them. In order to effectively using OGEV to jointly model discretionary destination, departure time and travel mode choices, a general framework that organizes the proposed modelling process is illustrated in Figure 3.1.

For specific discretionary trips, suppose an individual "i" who chooses jointly to travel to a specific discretionary destination "d", at specific departure time "t" and by a specific travel mode "m" from a choice set that has D\*T\*M alternatives where D, T and M are the total number of destinations, departure times and travel modes within the choice set respectively. Equation (3.1) shows the proposed form of the deterministic component for the underlying utility function.

$$V_{d,t,m} = ASC_{d,t,m}^{S} + \beta_X^{S} X_{d,t,m} + \beta_Z^{S} Z_i$$
(3.1)

where: V<sub>d,t,m</sub> deterministic utility of individual "i" for travelling to destination "d" at departure time "t" by using travel mode "m",

- $ASC^{S}_{d,t,m}$  alternative specific constant specific to alternative(s) S,
- X<sub>d,t,m</sub> vector of attributes of alternatives,
- Z<sub>i</sub> vector of individual i's characteristics,
- $\beta_X^s \& \beta_Z^s$  coefficients of X and Z variables, specific to alternative(s) S.

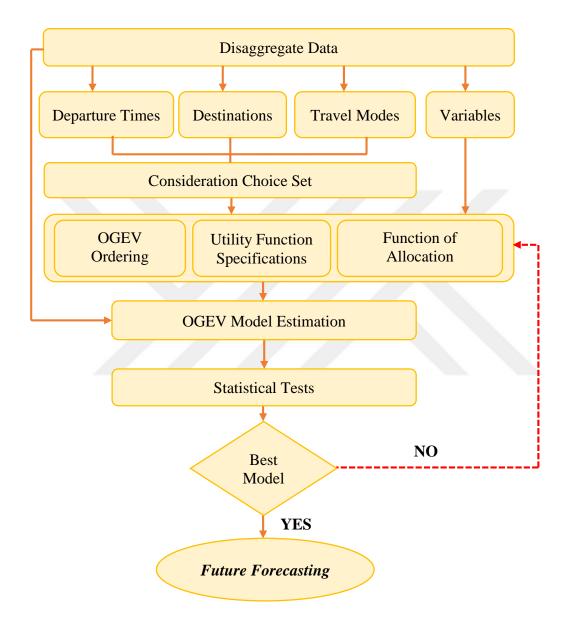


Figure 3.1 : OGEV proposed framework.

The proposed 2-level NL-OGEV model is structured as: destinations are allocated at the upper level with total number of branches equals D. The lower level consists of all possible combinations of departure times "t" and travel modes "m" that equal T\*M combinations. Additionally, the spatial correlation is represented by allowing some

elementary alternatives to overlap over the neighbouring destinations. Thus, the probability functions can be expressed as follows:

$$P(d, t, m) = \sum_{k=d}^{k=D} P(d, t, m|k) P(k)$$
(3.2)

$$P(d, t, m|k) = \frac{\left(\alpha_{d,t,m|k}\right)^{\frac{1}{\theta_{d,t,m|d}}} \exp\left(\frac{V_{d,t,m}}{\theta_{d,t,m|d}}\right)}{\exp(I_k)}$$
(3.3)

$$P(k) = \frac{\exp(\frac{\theta_{d,t,m|d}}{\theta_0} I_k)}{\sum_{k=d}^{k=D} \exp(\frac{\theta_{d,t,m|d}}{\theta_0} I_k)}$$
(3.4)

$$I_{k} = \log \sum_{d,t,m|k}^{D,T,M|k} (\alpha_{d,t,m|k})^{\frac{1}{\theta_{d,t,m|k}}} \exp\left(\frac{V_{d,t,m}}{\theta_{d,t,m|d}}\right)$$
(3.5)

where:  $\alpha_{d,t,m|k}$  the portion of existing of alternative "d,t,m" in nest "k" (allocation parameter),  $\theta_{d,t,m|d}$  error terms scale parameter of "d,t,m" conditional on "d",

- $\theta_0$  overall scale parameter (usually normalized to 1.0),
- I<sub>k</sub> Expected Maximum Utility of nest "k" (Inclusive value or log-sum value).

Moreover, a linear in parameters function that involves the effect of a specific variable has been used to distribute alternatives among different nests (i.e. allocation parameter) (Bhat et al, 1998). As shown in equation 3.6, rather than the intercept, a variable that may affect the value of allocation parameters will be considered. Indeed, a lot of available variables may be categorized as attributes for destinations that influence the similarities between alternatives in different nests such as travel time, travel cost and travel distance. Yet, in order to avoid adding complexities to the proposed model, only one of them has been considered.

$$W_{\alpha_{d,t,m|k}} = \gamma_{d,t,m} + \delta_{d,t,m} Y_{d,t,m}$$
(3.6)

where:	$W_{\alpha_{d,t,m k}}$	deterministic utility of allocation parameter of alternative		
		"d,t,m" conditional on destination "k"		
	$\gamma_{d,t,m}$	alternative specific constant specific to "d,t,m		
		alternative,		
	$\delta_{d,t,m}$	parameter of Y variable specific to "d,t,m" alternative,		
	Y <sub>d,t,m</sub>	a variable that affect the value of allocation parameter		
		alternative "d,t,m".		

The occurring of specific "d,t,m" alternative in a number of k's nests is depending on the proposed ordering pattern. For instance, if geographical location ordering is considered, thus, "d,t,m" alternative that is related to a destination "d" will occur in other adjacent alternatives which may be placed before or after "d". That is, according to the considered order of destinations, adjacent destinations will host common alternatives. However, the decision about the considered order of destinations is disputable. Notably, most of the previous researches adopted geographical locationbased (Geo-based) ordering which mainly relies on distances between destinations (Hassan et al, 2017). In this research, along with Geo-based ordering, an average travel time between origins and destinations (ATT OD-based) ordering is considered. Thus, this research establishes an important definition for the term closeness. We argue that the average travel times from origins to destinations offer a much better explanation which may lead to more plausible representation. The reason is, the in-between distances are not essential representing the actual approximation among destinations (they may do with high degree of certainty for private car trips) since in some cases closer destinations have much higher travel time especially for public transportation "pt" trips. This case may occur frequently in urban transportation systems that contain various "pt" facilities with a number of transfer centres and various accession points. Thus, in terms of "pt" trips, two geographically adjacent destinations may have extremely different travel times due to different "pt" accessibilities.

Another important advantage of using ATT OD-based ordering is that, it enables us to distribute elementary alternatives from the main destination to other destinations individually. That is, the investigation of ATT OD values across departure times and travel modes may result in some alternatives of one destination to have similar average travel time with others from another destination. For example, for a choice situation, only private car trips at morning peak departure times may be common for various

destinations; however, the same may not occur for other modes at different departure times. That makes the proposed approach more suitable for our choice situation since high degree of heterogeneity exists among alternatives within the same nest. By words, the proposed approach can enable us to assume various ordering patterns based on specific departure times and/or travel modes according to value of ATT across them. Therefore, in order to demonstrate our notion, two different sets of nesting structures are proposed to be constructed and tested: geographic location-based ordered set and average travel time OD-based ordered set.

Another significant approach that is adopted in this research is the applied specifications associated with explanatory variables of the deterministic utility. That is for all proposed OGEV structures, different specifications for model variables have to be proposed and tested in order to capture the best specification for each structure in terms of the magnitude of IV parameters, signs and degree of significance of parameters as well as the overall goodness of fit of the model. For each proposed structure, different combinations of generic and alternative specific variables have to be assumed. Notably, representing parameters that are specific to all of elementary alternatives will lead to a great number of estimates (i.e. DTM-1). Introducing this large number of estimates will not only add more encumbrances in estimation process but also complicate the interpretation of the results. Therefore, in an attempt to intuitively interpret the results of the estimation as well as ease the estimation process, the alternative specific variables (especially those related to individual characteristics) are proposed to be specific to one or more travel dimensions rather than the all elementary alternatives. For instance, in some specifications, the parameter of age variable may be specific to departure time alternatives, however, in other specifications, it may be assumed specific to destination or travel mode alternatives.

#### 3.5 Case Study

In this paper, the proposed framework is tested by using the shopping and entertainment trip data of Eskisehir city, Turkey. These data have been collected through a household survey that was conducted in 2015 in the context of Eskisehir Master Plan study which was operated by Eskisehir Metropolitan Municipality. Eskisehir city (Eskişehir in Turkish) is a city in north-western Turkey and the capital of the Eskişehir Province. It is considered as a medium sized city with a population of 799724 (2013 census) distributed over about 2678 km<sup>2</sup> area.

The considered shopping and entertainment trips data are a part of large-scale revealed preference data which include household and individual socio-demographics, individual's travel information, and attributes of used transportation mode. In the city, the most attracted shopping and entertainment activities are concentrated in three distinct regions (Figure 3.2) which are distinguished by having a lot of retail and entertainment activities. These regions can be named as ESPARK shopping centre (s), Ozdilek shopping centre (z) and Local Bazaar (l). Regarding departure time, it has been categorized into three different groups that differ in traffic conditions and availability of individual's free times (Table 3.1). In the context of travel mode, three modes that access to the three destinations and available during the three departure times have been considered in our analysis which are: private car (c), public bus (b) and tramway (t).

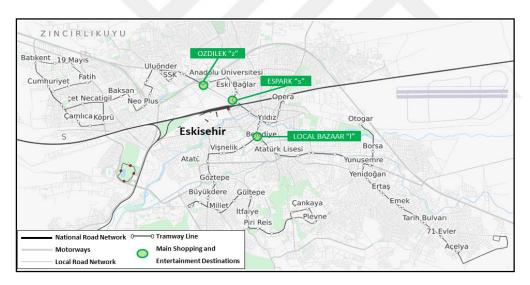


Figure 3.2 : Eskisehir city map.

<b>Table 3.1 :</b>	Categories	of departure time.
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Departure Time Periods	Time Intervals
Peak (p)	7.00 - 9.00 and 16.30 - 18.30
Off-peak (o)	9.00 - 16.30
Evening (e)	18.30 - 22.00*

\*observations after 22.00 have been neglected since they are trivial and happen after mandatory closing hours

There were a total of 529 observations. The distribution of individuals among available alternatives of each choice subset is shown in Table 3.2. Moreover, average travel time form origins to the considered destinations for private car and public transit users are shown in Table 3.3. Finally, Table 3.4 illustrates the explanatory variables that are considered in the estimated utility functions. Other variables related to the attributes of destinations such as number of shopping and entertainment activities might have significant effects, however, unfortunately, they were unavailable within collected data.

		# of Observations	Share(%)
	Peak (p)	104	19.66
<b>Departure Time (t)</b>	Off-Peak (o)	277	52.36
	Evening (e)	148	27.98
	Espark (s)	184	34.78
<b>Destination</b> (d)	Local Bazaar (l)	203	38.37
	Ozdilek (z)	142	26.84
	Car (c)	116	21.93
<b>Transportation Modes (m)</b>	Bus (b)	98	18.53
	Tramway (tr)	315	59.55

**Table 3.2 :** Distribution of sample among alternatives.

**Table 3.3 :** Average travel time from origins to considered destinations (ATT OD - minutes).

			Car "c"		Public Transportation "pt"				
Destination	Peak "p"	Off- peak "o"	Evening "e"	Average	Peak "p"	Off- peak "o"	Evening "e"	Average	
Espark (s)	33	32.9	28.3	31.4	37.9	31.7	33.2	34.3	
Ozdilek (z)	32.9	33	28.7	31.5	36	34.5	35.3	35.3	
Local Bazaar (l)	32	31	33.5	32.2	36	34.8	36	35.6	

<b>Table 3.4 :</b>	Model	variables.

Type of Variable	Abbreviation	Description	Unit
Alternative's Attribute	TT	Total Travel Time	Minutes
	TC	Total Travel Cost	Turkish Lira
	COW	Car Ownership	Dummy (0,1)
Traveller's	INC	Household Income	Turkish Lira
Characteristics	SS	Student Status	Dummy (0,1)
	AGE	Age of Individual	Years Old

#### **3.6 OGEV-Structures**

In order to model individuals' shopping and entertainment destination, departure time and travel mode choices in Eskisehir city, a number of OGEV structures is proposed and tested. Each proposed structure consists of two levels with 27 elementary alternatives. The upper level has three branches, one branch for each destination. Under each branch, a set of nine elementary alternatives (three departure times\*three modes) which are related to the considered destination are allocated. Moreover, according to the proposed spatial correlation pattern (destinations order), some elementary alternatives are common between multiple destinations. Figure 3.3 represents an example of one of the proposed OGEV structures.

As pointed before, the order of destinations can be a geographical location-based, an ATT OD-based or hybrid of both according to travel mode. This paper argues that hybrid sorting may lead to more representative OGEV structures especially for cases in which closer destinations have considerable different average travel times from origins. This situation can be clearly observed in our case study where, despite there is a remarkable closeness between Espark and Ozdilek rather than between Ozdilek and Local Bazaar (Figure 3.2), average travel time between OD of "pt" trips (Table 3.3) suggests another assembling. Practically, according to Figure 3.2, it may be convenient to assume similarities between Espark and Ozdilek. That aggregation is true for private car trips only since the average travel times of private car trips are almost the same for the three destinations over different departure times (Table 3.3). However, the average travel times of "pt" trips (bus and tramway) indicate that, a trip between Ozdilek and Local Bazaar may have much more common errors than a trip between Espark and Ozdilek through all times of day. An OGEV model can represent such hybrid similarities through assigning private car-departure time alternatives to be common within Espark and Ozdilek nests and assigning public transportationdeparture time alternatives to be common in Local Bazaar and Ozdilek nests.

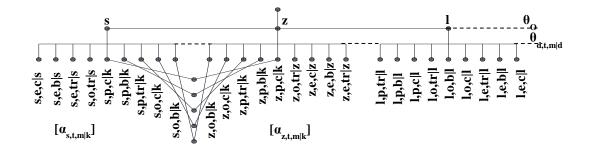


Figure 3.3 : Example for a geographical location-based OGEV structure.

Moreover, in order to express the dominance of the proposed ordering approach over other ordering patterns, some 'Geo-based only" and "ATT OD-based only" structures are estimated as well. Overall, four different OGEV structures are constructed and estimated (Table 3.5).

<b>Ordering Pattern</b>	Abbreviation	Description
Hybrid	NS_Hybrid	pt-based alternatives $\in$ "z" and "l" & c-based alternatives $\in$ "z" and "s"
ATT OD only	NS_ATT	pt-based alternatives $\in$ "z" and "l"
Geo-based only	NS_Geo1	$\forall$ d,t,m $\in$ "z" and "s" & $\forall$ d,t,m $\in$ "z" and "l"
Geo-based only	NS_Geo2	$\forall d,t,m \in "z" and "s"$

**Table 3.5 :** Proposed ordered nesting structure.

As illustrated in Table 3.5, NS\_Hybrid exhibits hybrid ordering patterns where public transit-based alternatives "pt-based" are common in both Ozdilek and Local Bazaar nests (average travel time-based ordering) and private car-based "c-based" alternatives are common in Espark and Ozdilek alternatives (geographical location-based ordering). In NS\_ATT, only the potential similarities between Ozdilek and Local Bazaar for public transportation-based alternatives are considered (only average travel time-based ordering). This structure ignores any similarities coming from adjacent locations and accounts only for the nearer average travel times. Therefore, it ignores the similarities of private car-based alternatives between Espark and Ozdilek. Besides, NS\_Geo1 and NS\_Geo2 completely ignore the average travel times-based assembling and consider only the geographical location for aggregating alternatives. By words, in NS\_Geo1, regardless of type of the transportation mode, similarities of Espark with Ozdilek from one side and Ozdilek with Local Bazaar from the other are assumed. In NS\_Geo2, however, a sole overlap between Espark and Ozdilek is proposed.

#### **3.7 Estimation Results**

The proposed OGEV structures were calibrated and estimated using the statistical package NLOGIT6. Regarding the scale parameter (dissimilarity), the overall scale parameter at top level is assumed to be equal to one (normalization). This specification requires lower level's scale parameters to be less than or equal to one to assure lesser variance of error terms for elementary alternatives and more than zero to ensure a convex log likelihood function.

Linear in parameter utility functions have been formulated and different determined specifications for their variables have been assumed and tested until reaching best models in terms of goodness of fit, signs, magnitudes and statistical significance of the estimates. The following equation represents the best utility function and its associated variables' specifications that contribute with best statistical arguments of the proposed OGEV structures.

$$V_{d,t,m} = ASC^{m} + b_{TT}^{t}TT + b_{TC}TC + b_{COW}^{m}COW + b_{INC}^{d}INC + b_{SS}^{m}SS + b_{AGE}^{t}AGE$$
(3.7)

where:	ASC <sup>m</sup>	travel mode alternatives specific constant
	b <sup>t</sup> <sub>TT</sub>	estimate of travel time parameter specific to departure time
		alternatives
	b <sub>TC</sub>	generic estimate of travel cost parameter
	$b_{\text{COW}}^{\text{m}}$	estimate of car ownership parameter specific to travel mode
		alternatives
	b <sup>d</sup> <sub>INC</sub>	estimate of income parameter specific to destination alternatives
	$b_{SS}^m$	estimate of student status parameter specific to travel mode
		alternatives
	$\mathbf{b}_{\mathrm{AGE}}^{\mathrm{t}}$	estimate of age parameter specific to departure time alternatives

In addition to this setting, different variables have been imposed individually in the utility function of allocation parameter. However, average trip distance (ATD) has been found to increase the overall goodness of fit and other statistical arguments with more intuitive values for allocation parameters (Equation 3.8).

$$W_{\alpha_{d,t,m|d}} = \gamma_{d,t,m} + \delta_{d,t,m} \operatorname{ATD}_{d}$$
(3.8)

where:  $ATD_d$  average travel distance from origins to destination "d"

Table 3.6 expresses the estimation results of the 4 accepted OGEV structures however Table 3.7 shows coefficient estimates of the allocation parameters for each structure.

	NS_Hybrid	NS_ATT	NS Geo1	NS Geo2
Constants	110_119.0114	110_1111		
Car Specific Alternatives	$-3.87(-5.43)^{a}$	-2.86(-5.82) <sup>a</sup>	$-3.26(-6.51)^{a}$	-1.93 (-5.75) <sup>a</sup>
Bus Specific Alternatives	$-1.19(-4.63)^{a}$	-0.9(-4.96) <sup>a</sup>	$-1.27 (-8.05)^{a}$	-0.60 (-6.34) <sup>a</sup>
Tram Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Total Travel Time	0.00 (1)	0100 (1)	0.000(1)	0100 (1)
Peak Specific Alternatives	-0.02(-3.34) <sup>a</sup>	-0.011(-3.64) <sup>a</sup>	-0.015(-3.90) <sup>a</sup>	-0.01(-2.82) <sup>a</sup>
Off-peak Specific Alternatives	$-0.02(-3.54)^{a}$		-0.013(-3.10) <sup>a</sup>	-0.004(-1.6) <sup>b</sup>
Evening Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
<u>Total Travel Cost</u>	0.00 (1)			
<u>(Generic-TL)</u>	$-0.24(-5.17)^{a}$	$-0.032(-1.75)^b$	$-0.124(-3.74)^{a}$	$-0.17 (-7.72)^a$
<u>Car Ownership (F=0&amp;T=1)</u>				
Car Specific Alternatives	3.38(4.64) <sup>a</sup>	$2.56(5.1)^{a}$	3.00 (6.17) <sup>a</sup>	1.57 $(4.85)^a$
Bus Specific Alternatives	0.00 (F)	2.30(3.1) 0.00 (F)	0.00 ( <b>0.1</b> 7)	0.00 (F)
Tram Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Age (Years Old)	0.00(1)	0.00(1)	0.00 (1)	0.00(1)
Peak Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 (F)
Off-peak Specific Alternatives	$0.00(1)^{a}$	0.00(1) $0.02(4.93)^a$	0.00(1) $0.021(4.96)^a$	$0.00(1)^{a}$
Evening Specific Alternatives	0.00 (F)	0.00 (F)	0.00 (F)	0.00 ( <b>4.</b> 07)
Income (1000TL/Month)	0.00(1)	0.00(1)	0.00 (1)	0.00 (1)
Espark Specific Alternatives	NA	NA	0.00 (F)	NA
Ozdilek Specific Alternatives	NA	NA	0.00 (F)	NA
Local Bazaar Specific Alt.	NA	NA	$-0.081 (1.72)^{b}$	NA
Student Status (0& 1)			00001 (10.2)	
Car Specific Alternatives	NA	NA	-1.24 (-3.08) <sup>a</sup>	NA
Bus Specific Alternatives	NA	NA	0.00 (F)	NA
Tram Specific Alternatives	NA	NA	0.00 (F)	NA
Value Of Time (US Dollar/hr.)				
Peak Specific Alternatives	2.50	10.30	3.625	1.75
Off-peak Specific Alternatives	1.250	8.45	2.90	0.705
Evening Specific Alternatives	0.00	0.00	0.00	0.00
Scale Parameters (IVP)	- · ·			
$\theta_{s,t,m s}$	0.73(5.27) <sup>a</sup>	0.70 (3.39) <sup>a</sup>	0.76 (10.64) <sup>a</sup>	0.88 (5.15) <sup>a</sup>
$\theta_{z,t,m z}$	0.25 (F)	0.333 (F)	0.57 (1.66) <sup>b</sup>	0.25 (F)
$\theta_{l,t,m l}$	1.00 (8.24) <sup>a</sup>	0.65 (6.01) <sup>a</sup>	1.00 (F)	0.71 (2.74) <sup>a</sup>
Goodness of Fit	,	()		
# of Observations	529	529	529	529
# of parameters	41	33	43	40
LL(β)	-1517.20	-1541.00	-1531.65	-1524.18
$\frac{(r)}{LL(0)}$	-1743.50	-1743.50	-1743.50	-1743.50
LL(C)	-1623.40	-1634.33	-1610.74	-1618.80
LL(3-level)	-1535.17	-1535.17	-1535.17	-1535.17
LL(MNL)	-1550.24	-1550.24	-1540.02	-1550.24
-2LL(βvs.C)	212.4	186.66	158.18	189.24
Adjusted $\rho^2$	0.12	0.1	0.11	0.1
-2LL(OGEV vs. 3-level)	35.94	-11.66	7.04	22.00

**Table 3.6 :** The coefficient estimates for the proposed OGEV structures.

F=Fixed Parameter, NA = Not Applicable <sup>*a*</sup> Significant at 95% level, <sup>*b*</sup> Significant at 90% level, t-statistics in parentheses

			NS_	Hybri	d		NS	S_AT	Г		NS	_Geo1			NS_	Geo2	
	k		S	Z	1		s	Z	1		S	Z	1		S	Z	1
	$\alpha_{s,c,p\mid k}$		0.94	0.06	0		1	0	0		0.92	0	0.08		0.99	0.01	0
	$\alpha_{s,b,p\mid k}$		1	0	0		1	0	0		1	0	0		0.68	0.32	0
(S)	$\alpha_{s,tr,p\mid k}$		1	0	0		1	0	0		1	0	0		0.72	0.28	0
ed (	$\alpha_{s,c,o\mid k}$	0.93	0.78	0.22	0	0.70	1	0	0	0.96	0.7	0.3	0	0.88	0.83	0.17	0
-bas	$\alpha_{s,b,o\mid k}$	) = s	1	0	0		1	0	0	11	0.72	0.28	0	s = (	0.55	0.45	0
Espark-based (s)	$\alpha_{s,tr,o k}$	$\theta_{s,t,m\mid s} =$	1	0	0	$\theta_{s,t,m\mid s} =$	1	0	0	$\theta_{s,t,m s}$ :	0.8	0.2	0	$\theta_{s,t,m\mid s} = 0$	0.38	0.62	0
Est	$\alpha_{s,c,e\mid k}$	θ	1	0	0	θ	1	0	0	θ	1	0	0	θ	0.99	0.01	0
	$\alpha_{s,b,e\mid k}$		1	0	0		1	0	0		0.97	0.03	0		1	0	0
	$\alpha_{s,tr,e k}$		1	0	0		1	0	0		1	0	0		0.94	0.06	0
	$\boldsymbol{\alpha}_{z,c,p k}$		0.83	0.17	0		0	1	0		0.8	0.03	0.17		0.86	0.14	0
	$\alpha_{z,b,p\mid k}$		0	1	0		0	1	0		0	1	0		0.03	0.97	0
(z)	$\alpha_{z,tr,p k}$		0	0.77	0.23	~	0	0.65	0.35		0	1	0		0.05	0.95	0
sed	$\boldsymbol{\alpha}_{z,c,o k}$	0.25	0.95	0.05	0	= 0.333	0	1	0	0.57	0.88	0.12	0	0.25	0.79	0.21	0
c-ba	$\boldsymbol{\alpha}_{z,b,o k}$	11	0	0.56	0.44	= 0	0	0.4	0.6	11	0.47	0.53	0	z = 0	0.44	0.56	0
Ozdilek-based (z)	$\alpha_{z,tr,o\mid k}$	$\theta_{z,t,m z}$ :	0	0.85	0.15	$\theta_{z,t,m z}:$	0	0.5	0.5	$\theta_{z,t,m\mid z}:$	0.02	0.97	0	$\theta_{z,t,m\mid z} = 0$	0.39	0.61	0
Ozo	$\alpha_{z,c,e\mid k}$	$\oplus$	0	1	0	θ	0	1	0	9	0	0.97	0.03	Ð	0.43	0.57	0
	$\alpha_{z,b,e\mid k}$		0	0.49	0.51		0	0.4	0.6		0.74	0.26	0		0	1	0
	$\alpha_{z,tr,e\mid k}$		0	0.82	0.18		0	0.42	0.58		0	0.9	0.1		0.25	0.75	0
	$\alpha_{l,c,p\mid k}$		0	0	1		0	0	1		0	0.14	0.86	1	0	0	1
]	$\alpha_{l,b,p\mid k}$	1	0	0.17	0.83		0	0.39	0.61		0	0	1		0	0	1
ed (	$\alpha_{l,tr,p\mid k}$		0	0.25	0.75		0	0.06	0.94		0	0	1		0	0	1
-bas	$\alpha_{l,c,o\mid k}$	1.00	0	0	1	0.85	0	0	1	1.00	0	0	1	0.71	0	0	1
zaar	$\alpha_{l,b,o\mid k}$	11	0	0.14	0.86	11	0	0.1	0.9	11	0	0	1	11	0	0	1
Local Bazaar-based (1)	$\alpha_{l,tr,o\mid k}$	$\theta_{l,t,m l}$	0	0.91	0.09	$\theta_{l,t,m 1} =$	0	0.69	0.31	$\boldsymbol{\theta}_{l,t,m l}$	0	0	1	$\theta_{l,t,m l} =$	0	0	1
ocal	$\alpha_{l,c,e\mid k}$		0	0	1		0	0	1		0	0.9	0.1		0	0	1
Γ	$\alpha_{l,b,e\mid k}$		0	0.61	0.39		0	0.48	0.52		0	0	1		0	0	1
	$\alpha_{l,tr,e\mid k}$		0	0.89	0.11		0	0.59	0.41		0	0.96	0.04		0	0	1

 Table 3.7 : Coefficient estimates of allocation parameters for the proposed OGEV structures.

The following points summarize most substantial analyses and conclusions that are extracted from Table 3.6:

• In terms of overall goodness of fit, all models achieve acceptable Log Likelihood (LL) ratio for convergence versus constant only model. Yet, highest value is associated with the NS\_Hybrid (212.4). That result is supported by the value of rho-squared as well (0.12). Additionally, compared with (MNL), the four ordering patterns seem to be significantly better than it. Further, compared with 3-level NL, all ordering structures show better LL except NS\_ATT where a smaller LL has been reached.

- The values of the scale parameters are between zero and one for all models. Furthermore, the estimates of them are significantly different than zero.
- The parameters of total travel time (specific to departure time) are found to be significantly different than zero at 90% level of significance with expected negative sign in all models. However, NS\_ATT and NS\_Geo1 result in less convenient magnitudes since the influence of peak period travel times is slightly higher than off-peak period travel times. Indeed, most of the mode choice modelling literature support that individuals may put much more emphasis on travel time in peak periods rather than off-peak due to the extreme increase in congestion rates (Bhat, 1998).
- As a generic parameter, total travel cost rationally occurs in negative sign with magnitudes that are statistically significant at 90% level of significance for all of four structures. Yet, in all models except NS\_ATT, relative to the parameter of total travel time, individuals in Eskisehir city may give more importance to cost rather than time while performing shopping and entertainment trips.
- The relative effect of travel time and traffic cost can be easily conveyed in a more accurate manner through calculating the value of time "VOT". By reviewing their values, VOT estimates associated with NS\_ATT are found to be too high (10.30 and 8.45 USD/hr for peak trips respectively). Still, NS\_Hybrid and NS\_Geo1 result in more plausible values (2.50 and 3.625 USD/hr for peak trips respectively). Obviously, for shopping and entertainment trips in Eskisehir city, travellers have more willingness to pay for saving their trip time in peak periods than in off-peak and evening periods. Notably, the zero-value associated with evening period comes from fixing evening alternatives-specific travel time parameter at zero (i.e. base alternatives).
- The value of car ownership estimates (specific to travel mode) show an inclination towards performing shopping and entertainment trips by using private car rather than public transportation if the individual owns car(s).
- The off-peak alternatives-specific age coefficients are found to be significantly higher than zero for all OGEV structures. Obviously, elderlies like to perform shopping and entertainment trips through off-peak periods rather than other times of day.

- For monthly income variable, all applied specifications have not resulted in accepted estimates in all structures except NS\_Geo1. The Local Bazaar destination-specific parameter of monthly income is significantly less than zero. This parameter leads to a reasonable interpretation where the negative sign implies that high-income individuals more likely make their shopping and entertainment trips in shopping centres rather than local bazaars.
- Like monthly income, student status variable results in significant estimates for NS\_Geo1 only. A significant and negative car alternatives-specific coefficient implies that, as expected, students are more likely to use public transportation over private car while heading to shopping and entertainment destinations.

Another significant output that may lead to crucial conclusions is the value of allocation parameters (Table 3.7). Obviously, the values of allocation parameter  $(\alpha_{t,d,m|k})$  can be clearly interpreted through analysing it along with scale parameters  $(\theta_{d,t,m|d})$ . That can guide to the following important deductions:

- For all OGEV structures, comparing with Ozdilek, the values of scale parameters associated with Espark and Local Bazaar destinations are closer to one. That suggests lesser correlation among alternatives allocated in Espark or Local Bazaar nests. However, alternatives in Ozdilek nest may have higher correlation.
- On the other hand, the magnitudes of allocation parameters indicate that some alternatives have more probability to be in a less or more correlated nest rather than in their mother nest. For instance, the alternative of "travelling to Ozdilek at peak hour by using car" is more likely to be with Espark nest rather than Ozdilek ( $\alpha_{z,c,p|s} = 0.83$ ). This may imply that this alternative may have less correlation with other Ozdilek alternatives ( $\alpha_{z,c,p|z} = 0.17$ ).
- In NS\_Hybrid, the relative values of  $\alpha_{d,t,m|k}$  reveal some potential dependencies between Ozdilek-based and Local Bazaar-based alternatives. For example, travelling by tramway at peak period to Ozdilek has 23% probability to be similar with traveling by the same mode at the same time but to Local Bazaar as a neighbouring destination. In NS\_ATT, strong interaction between alternatives of Ozdilek and Local Bazaar destinations is expected because values of  $\alpha_{d,t,m|k}$  are relatively close. For instance, high

correlation may exist between Ozdilek and Local Bazaar for "departing at evening times by using bus" since values of  $\alpha_{d,t,m|k}$  suggest considerable interaction (e.g.  $\alpha_{z,tr,e|z} = 0.42$  and  $\alpha_{z,tr,e|l} = 0.58$ ).

- For, NS\_Geo1, only three elementary alternatives have common effects between Espark and Ozdilek: car-off peak, bus-off peak and tramway-off peak. Opposite to previous structures, very low similarities are observed between Ozdilek and Local Bazaar nests. Notably, unlike travel time-based ordering, considering the geographical ordering of destinations does not lead to a proper representation.
- Finally, NS\_Geo2 exhibits similarities produced from geographical order of Espark and Ozdilek only. The values of α<sub>d,t,m|k</sub> suggest more substantial mutual effects of alternatives among both nests. Notably, connecting only Espark with Ozdilek has some uncertainties of expressing spatial correlation in a clear way. The reason is, being a shopping mall rather than local retails is another important attribute of Espark and Ozdilek which may lead to significant common error terms between them.

Overall, signs and magnitudes of the utility functions' coefficients, value of time, overall goodness of fit and associated allocation parameters, lead to accepting the NS\_Hybrid model as the best destinations' spatial correlation representative model. That supports the proposed approach of adopting the average travel time between origins and considered destinations ordering rather than geographical location ordering only.

#### 3.8 Conclusion

This paper proposes the using of the discrete OGEV approach to represent discretionary destinations along with departure times and travel mode choices under a unified framework. We argue that individuals when decide on discretionary trips are more likely choose these three dimensions in a joint fashion rather than independently as traditional four-step model assumes. Moreover, the OGEV model can provide a better and simpler representation of the potential spatial correlation within various destinations. Further, the paper embraces a hybrid ordering pattern in which different bases for the order of destinations can be adopted. That is, along with the conventional geographical location-based ordering, an average origin-destination travel time-based

ordering can be considered as well. That can represent readily the heterogeneity in individuals' perceptions toward urban discretionary destinations while evaluating different departure times and travel modes. By words, the proposed approach allows the spatial correlation between destinations to differ from time to time and travel mode to another rather than assuming identical correlation pattern across them.

The proposed approach has been examined by using shopping and entertainment trips data of Eskisehir city, Turkey. Practically, four different OGEV structures that represent different ordering patterns among main shopping destinations in the city have been constructed and associated models have been estimated. In the light of estimation results, the following crucial conclusions have been reached:

- While performing shopping and entertainment trips, individuals jointly decide on, "to which destination", "at which time" and "by which mode" rather than independently. This could be discovered by examining the existence of statistical correlations among those three travel dimensions. This assumption has been proved in our case study where all proposed OGEV structures have been statistically significant. Neglecting such dependencies (as adopting in traditional four-step model) means misrepresentation of actual travellers' behaviour for such kind of trips which certainly lead to significant forecasting errors and distorted policy implications.
- Moreover, around all proposed OGEV structures, hybrid-ordering pattern has shown best performance in terms of overall goodness of fit, signs of estimates, values of scale parameters and value of allocation parameters. That can usefully help planners to clearly understand individuals' behaviour which leads finally to proper policies and plans. For instance, the superiority of hybrid ordering pattern implies that individuals while deciding on performing shopping and entertainment trips, are more likely decide on destination firstly with correlation between destinations that have similar travel times. Consequently, they capture proper departure time and travel mode. Therefore, in order to mitigate congestion that is produced from such type of trips, transportation planners could suggest spatial-based measures rather than temporal-based ones.

- On the other hand, the proposed hybrid ordering pattern provides detailed analyses about the inter-relationships associated with various discretionary destinations, departure times, and travel modes where traditional-four step model cannot. That leads to more certain, specific, efficient and precise policy decisions. For example, in Eskisehir city, while performing shopping and entertainment trips, public transportation users perceive common unobserved utility for Ozdilek and Local Bazaar destinations. On the other hand, private car users perceive similarities for Espark and Ozdilek. Thus, policies that encourage the using of public transportation will lead to entirely different results than policies that restrict the using of private car.
- Finally, one significant restriction of the proposed framework is, it is applicable for limited number of alternatives (e.g. limited number of destinations) where extreme difficulty would be added to the estimation process as the number of alternatives increases. However, it may represent more effective and accurate alternative of the first three stages in traditional four-step model while analysing discretionary trips for small or medium sized cities where only a limited number of discretionary destinations exists.



# 4. MODELLING DEPARTURE TIME, DESTINATION AND TRAVEL MODE CHOICES BY USING THE GENERALIZED NESTED LOGIT MODEL: DISCRETIONARY TRIPS <sup>3</sup>

#### 4.1 Abstract

Despite traditional four-step model is the most prominent model in majority of travel demand analysis, it does not represent the potential correlations within different travel dimensions. As a result, some researches have suggested the using of choice modelling instead. However, most of them have represented travel dimensions individually rather than jointly. This research aims to fill this gap through employing the Generalized Nested Logit model for jointly representing three major travel dimensions; destination, departure time and travel mode. The suggested research methodology depends mainly on agglomerating alternatives that have similar error term's variances within specific gaps under common nests without any imposed restrictions. Moreover, different variance gaps lead to overlapped nesting system which can enable analysers modelling inner- and inter-correlation. The proposed approach has been examined through modelling individuals' choices among the main shopping destinations in Eskisehir city, Turkey. In the light of estimation results, the proposed model attains a relatively good over-all goodness of fit which reflects a more prominent predictability power. Moreover, individuals in Eskisehir have been found perceiving more interest to the cost rather than time. From another hand, a behaviour of trading-off between performing such trips at peak periods by using transit or making them at off-peak by private car has been detected.

<sup>&</sup>lt;sup>3</sup> This chapter is based on the paper "Modelling Departure Time, Destination and Travel Mode Choices by Using the Generalized Nested Logit Model: Discretionary Trips", International Journal of Engineering (IJE), IJE TRANSACTIONS B: Applications, Vol. 33, No. 2, (February 2020), 186-197.

## 4.2 Nomenclature

U	Total random latent utility function	INC	Household monthly income
V	Deterministic component of the latent utility	SS	Student status (1 if student 0 otherwise)
ASC	Alternative specific constant	AGE	Age of the traveller
Q	Vector of alternative's attributes	t, d and m	departure time, destination and travel mode respectively
С	Vector of decision maker's characteristics	Greek Syml	pols
Ι	Inclusive value (Maximum Expected Utility)	α	allocation parameter
b	Parameter estimate of an explanatory variable	β	Vector of coefficients for decision maker's characteristics
f	specific trip dimension(s)	8	Error term or random component unknown to the analyst
P[·]	Probability of choosing a specific alternative	£`	Error term associated with a specific nesting level
$R_1$	Large scale parameters' range	θ	Scale parameter of an Extreme Value Distribution
$\mathbf{R}_2$	Medium scale parameters' range	Subscripts	
<b>R</b> <sub>3</sub>	Small scale parameters' range	t,d,m	Joint choice of a departure time "t", destination "d" and travel mode "m"
TT	Total travel time	x,y,z	Joint choice of a departure time "x", destination "y" and travel mode "z"
TC	Total travel cost	n	A decision maker
COW	Car ownership	i, j, k	GNL nests that have difference in scale parameters within ranges $R_1$ , $R_2$ and $R_3$ respectively

## **4.3 Introduction**

The world population rapid increment requires modern transportation demand strategies (Sumia and Ranga, 2018). However, transportation demand forecasting introduces a very essential stage that affects directly the selection of different management policies (Ghasemi and Rasekhi, 2016). Since 1940s, transportation planning studies rely primarily on travel demand forecasting models (Johnston, 2004). Nevertheless, the real concern towards travel demand models has started in US in 1960s (Morehous, 1969). From that date, four-step model has become the major object of most transportation planning studies due to its relative simplicity (Gu, 2004; Boyce, 2002). However, some lacks associated with the fixed order of stages, aggregate orientation, and neglecting characteristics of decision makers in most steps, have made four-step model under some criticism (Elmorssy and Tezcan, 2019).

Considering the trip distribution stage, over years, various methods for the distribution of trips among destinations have been developed such as growth factor method, gravity models, and destination choice models (Ortuzar and Willumsen, 2011). Despite the

fact that destination choice models show better performance in terms of goodness of fit and predictability than other traditional models, all of such models ignore the potential interaction between destination choice and other travel dimensions that may exist inside the choice set. For example, through congested networks, all destination distribution models assume compensations between closer destinations. However, for discretionary trips, individuals may shift their departure times or change the travel modes to travel to their desired destinations. Thus, for such kind of trips, deeming the mutual interaction between destination choice from one side, departure time and travel mode choices from the other is a prerequisite in order to properly evaluate different policy measurements that aim to mitigate traffic congestion and accurately forecast their associated consequences. That can be sufficiently attained through advanced choice models that consider for the potential correlation that may exist between alternatives belonging to same or different travel dimensions (Hassan et al, 2017; Bhat, 1998).

As there is a gap in literature about representing a unified choice model that connects different travel demand dimensions and consider potential correlations between them, this research aims to contribute to filling this gap through proposing the application of the Generalized Nested Logit (GNL) model in jointly representing destination, departure time and travel mode dimensions of discretionary trips. The proposed framework can be represented as a more accurate and efficient alternative for the first three steps in traditional four-step model especially when it is applied to discretionary trips for small and medium scale forecasting and planning issues.

## 4.4 Background

Nowadays, the methodology of four-step model is almost universally known and applied in most of the aggregate trip-based analyses (e.g. master plans) (McNally, 2000). However, despite the widespread usage, the four-step travel demand forecasting model has some improper assumptions such as; the fixed sequence of steps among individuals (Oppenheim, 1995), neglecting the effects of decision makers' characteristics (Vuchic, 2005), missing the influences of congestion on the travel time (Johnston, 2004).

In order to overcome such restrictions, some researches have directed their interest toward using choice modelling approach as an alternative for some or all of the stages in four-step model. Indeed, choice modelling approach is usually used only at the modal split stage in most of the traditional four-step models with a little use in the trip distribution stage which is dominated by gravity models (McNally, 2000). Recently and slowly, discrete choice models have been introduced as an alternative for gravity models for modelling destination choice and other travel choices (e.g. mode choice) either as a part of the four-step model like in Pozsgay and Bhat (2001) or independently as in activity-based models (Bhat et al, 1998; Miller and O'Kelly, 1983). Through the following paragraphs, we shed the light on some researches that focused on introducing various spatial and temporal travel dimensions (e.g. destination and departure time) under the context of choice modelling.

Regarding destination choice modelling, despite there are abundant studies that account for it, most of them were in fields other than transportation (Hassan et al, 2017). For example, in tourism, Seddighi and Theocharous (2002) have examined individuals' destination choices for recreational travels. Similarly, Shaw and Ozog (1999) have developed a Hybrid nested Multinomial Logit model that represents destination choices for overnight entertainment activities. Moreover, Eymann and Ronning (1997) analysed touristic international destination choices in Germany through developing a Nested Logit model. In the area of business, Lewis et al (2010) introduced a discrete destination choice model for young individuals' travels during holidays in Australia. In the field of consumer behaviour, a comparative study of single and multiple objective entertainment destinations has been introduced by Yeh et al (2001).

From another hand, it is crucial to model departure time along with other travel dimensions (e.g. destination and travel mode) in order to better represent the interrelationship between congestion and trips' distribution over time in a day (Gu, 2004). Regarding departure time scale, some studies have adopted discrete choice-based models such as Bhat (1988) who jointly modelled travel mode and departure time through a hybrid Multinomial- Ordered Generalized Extreme Value (MNL-OGEV) discrete choice model. Bates et al (2001) have reviewed the reliability for traveller's departure time by using the discrete approach as well. Elmorssy and Tezcan (2019a and 2019b) have examined the inter-correlation between departure time, destination and travel mode by using discrete NL models. In contrast, other researchers have developed continuous time choice-based models such as; Bhat (2005 and 2008) who formulated a multiple discrete-continuous Extreme Value (MDCEV) Model in which discrete travel mode choice is connected with continuous departure time choice without considering for correlation between error terms among both dimensions. This model has been enhanced later by Pinjari and Bhat (2010) to relax the assumption of independency between error terms by connecting both travel dimensions via NL model which called multiple discrete-continuous Nested Extreme Value (MDCNEV) model.

Reviewing literature that represented joint choice of multiple travel dimensions (e.g. departure time, destination, travel mode, etc.) leads to conclude that most of them have used Nested Logit (NL) model, to connect such dimensions since it results in closed form expressions for choice probability (Elmorssy and Tezcan, 2019b; Yagi and Mohammadian, 2010). However, more advanced approaches that may better account for correlations between error terms (e.g. Mixed Logit) require a cumbersome simulation-based estimation procedure (Pinjari and Bhat, 2010).

From another hand, the basic NL model which is used extensively in most travel demand modelling applications is the two-level NL model (Hensher, 2005), however, other multi-level structures (e.g. three-level) have been used in limited number of researches (Elmorssy and Tezcan, 2019a; Cascetta, 2005, Bowman and Ben-Akiva, 2001). Such advanced NL structures, when applied to jointly represent various travel dimensions, differ in representing the correlation patterns as well as the degree of complexity (Cascetta, 2005). By words, while simpler models (e.g. two-level NL) provide less complicated computational powers, they consist of a set of assumptions that limits the number of considered correlation schemes. In contrast, more advanced models (e.g. three-level, four-level NL and CNL) can represent various correlation structures; however, they are seldom applicable due to their complicated estimation processes. From another hand, such models have not enough flexibility to represent inner-correlation (interdependence) within travel dimension(s) (e.g. correlation between similar travel modes) along with the correlation among different travel dimensions.

An approach which gathers both estimation simplicity and flexibility in introducing various potential correlation patterns is the GNL model (Chieh-Hua and Koppelman, 2001).GNL allows each alternative to occur with any other alternatives in any number

of nests with a specific portion (i.e. allocation parameter) based on the real correlations existed within the sampled data. This paper argues that, an efficient joint model for departure time, destination and travel mode choices can be attained through using the GNL model.

#### 4.5 Proposed Methodology

In GNL model, alternatives are free to occur with any other alternatives in any number of nests regarding or regardless of the rational interpretation of that aggregation. By words, the one thing that controls correlation patterns is the sample itself rather than assumptions of logically potential interactions between alternatives. Hence, it is not necessary for aggregated nests to be related to rational reading. For example, it is possible to observe relative similarities between all alternatives related to the same travel dimension (e.g. the same departure time) which can be read in a logical way. On the other hand, a correlation between different departure times with different destinations and various transportation modes which is uninterruptable may be discovered in the sampled data. The source of such correlation is due to unobserved common properties which are unknown to the analyst; however, accounting them may enhance the forecasting capability of the model. Fortunately, GNL model has the ability of introducing such phenomena. The following chart (Figure 4.1) illustrates a proposed methodology that is used to model departure time, destination and travel mode jointly under a GNL structure.

For a specific discretionary trip choice situation, a decision maker "n" chooses simultaneously to depart at time "t", head towards destination "d" by using travel mode "m", where  $t \in S_t = [t_1, t_2, t_3, ..., t_n, ..., t_T]$ ,  $d \in S_d = [d_1, d_2, d_3, ..., d_n, ..., d_D]$  and  $m \in S_m$  $= [m_1, m_2, m_3, ..., m_n, ..., m_M]$ . The total number of mutually exclusive alternatives within the consideration set is T\*D\*M alternatives. The total perceived utility of choosing t, d, and m alternatives is  $U^n_{t,d,m}$ . For the sake of simplicity, the abbreviation "n" is dropped down from all equations so that, the utility associated with decision maker "n" is  $U_{t,d,m}$ . Equations 4.1 and 4.2 represent the general form of the total random utility associated with alternatives.

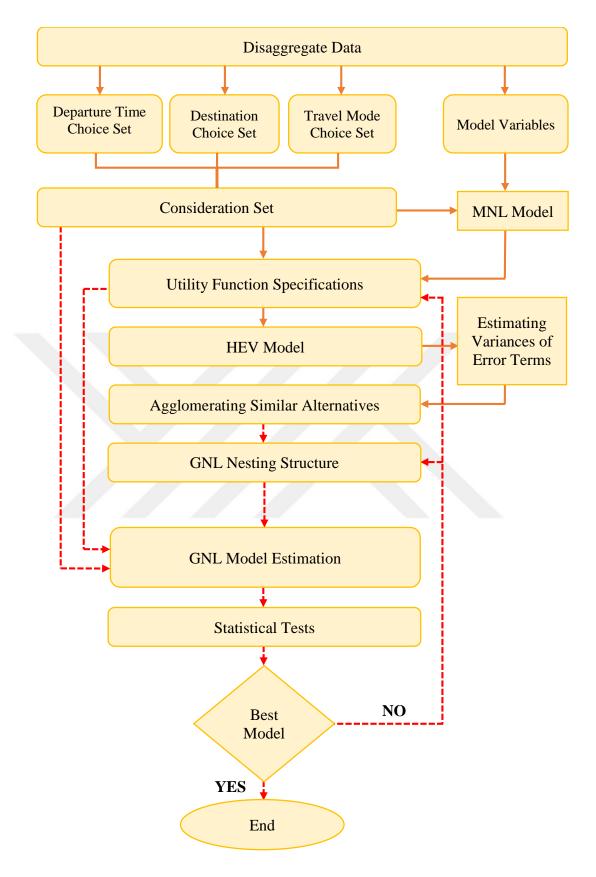


Figure 4.1 : General framework of the proposed approach.

$$U_{t,d,m} = V_{t,d,m} + \mathcal{E}_{t,d,m|j} + \mathcal{E}'_{j} + \ln \alpha_{t,d,m|j}$$

$$(4.1)$$

$$V_{t,d,m} = ASC_{t,d,m} + \beta_Q * Q_{t,d,m} + \beta_C * C^n$$

$$(4.2)$$

The GNL probability function, of choosing "t, d, m" that occurs in a number of nests (1,2,3,...,i,...,j,...,k,....J) through a GNL structure with total number of nests equals "J", can be expressed as follows;

$$P[t, d, m] = \sum_{j=1}^{J} \frac{\exp\left(\frac{\Theta_{t,d,m|j}}{\Theta_{j}} * I_{j}\right)}{\sum_{j=1}^{J} \exp\left(\frac{\Theta_{t,d,m|j}}{\Theta_{j}} * I_{j}\right)}$$

$$* \frac{\alpha_{t,d,m|j}^{\frac{1}{\Theta_{t,d,m|j}}} \exp\left(\frac{V_{t,d,m}}{\Theta_{t,d,m|j}}\right)}{\sum_{t_{n},d_{n},m_{n}|j}^{t_{n},d_{n},m_{n}|j} \alpha_{t_{n},d_{n},m_{n}|j}^{\frac{1}{\Theta_{t,d,m|j}}} \exp\left(\frac{V_{t_{n},m_{n},d_{n}}}{\Theta_{t,d,m|j}}\right)}$$

$$(4.3)$$

and;

$$I_{j} = \ln \sum_{t_{n}, d_{n}, m_{n} \mid j}^{t_{T}, d_{D}, m_{M} \mid j} \alpha_{t_{n}, d_{n}, m_{n} \mid j}^{\frac{1}{\theta_{t, d, m \mid j}}} \exp\left(\frac{V_{t_{n}, m_{n}, d_{n}}}{\theta_{t, d, m \mid j}}\right)$$
(4.4)

That leads to a covariance between any pair of alternatives (t, d, m and x, y, z) to be;

Cov(t, d, m and x, y, z) = 
$$\frac{\pi^2}{6} \sum_{j=1}^{J} \sqrt{\alpha_{t,d,m|j} \alpha_{x,y,z|j}} \left(\theta_j^2 - \theta_{\cdot|j}^2\right)$$
 (4.5)

Regarding the utility function and its associated explanatory variables, as the number of elementary alternatives increases, adopting alternative specific coefficients will result in a large number of estimates (i.e. D\*T\*M-1) which add more encumbrances in the estimation process and also complicate the interpretation of the results. Therefore, the alternative specific variables are proposed to be specific to travel dimension(s) rather than to all elementary alternatives. In order to reach the best set of specifications that may be used initially in estimating the GNL model, a traditional Multinomial Logit (MNL) model is proposed to be estimated at first to capture the best specifications that lead to best MNL parameters in terms of magnitudes, signs and degree of significance as well as the overall goodness of fit.

As illustrated previously, the GNL model provides satisfactory flexibility for alternatives to occur with any other alternatives in any number of nests according to the correlation patterns within the sampled choice data. In order to clearly recognize the correlation patterns existing within a set of discretionary choice data, the Heteroscedastic Extreme Value (HEV) model that was proposed by Hensher (1999) is proposed to be utilized. The proposed method is based on estimating a HEV model which assumes independent but non identical extreme value distribution for error terms of all elementary alternatives. Therefore, the value of scale parameters associated with alternatives can provide very useful conceptions about the existing correlation patterns. That is, alternatives which have their scale parameter in a specific range can be gathered in one group or nest. Further, changing the proposed range by decreasing or increasing it can divide or expand the produced nests into other bigger or smaller ones which yields the number of inter-correlated sets of alternatives.

A critical point related to this approach is; the ranges of scale parameters (or variances) that will be proposed to aggregate alternatives into nests are still ambiguous. In this paper, we purpose an empirical method by which initial accurate values of similar variances' ranges can be easily reached. These initial values can be used to find preliminary interacted groups (overlapped nests) from the elementary alternatives. The main idea of the proposed method is dividing the difference between minimum and maximum variance (i.e. the gap of variances) by distinct values to compute different ranges of variances (Equation 4.6). The three ranges  $(R_1, R_2 \text{ and } R_3)$  given in Equation 4.6 can roughly refer to the sets of elementary alternatives that are suggested to be gathered under the same nest (Equation 4.7). Moreover, the using of three steps that differ from small to wide ranges will result in representing various levels of correlation among elementary alternatives. By words, in order to firstly get a small step that can capture inner-correlation in-side of each travel dimension, the variance gap is suggested to be divided by the total number of alternatives produces from combining all travel dimensions. For a medium step, to calculate the value that may extract interactions between various travel dimensions; the gap is divided by the average number of joint alternatives from two different travel dimensions rather than the three.

Consequently, a wider step that may separate alternatives according to each travel dimension can be attained through dividing the gap over the total number of travel dimensions which is three in our choice situation.

$$Variance Ranges \begin{cases} R_{1} = \frac{\pi^{2}}{6} * \frac{Gap \text{ of Scale Parameters}}{\text{Total Number of Elementary Alternatives}} \\ R_{2} = \frac{\pi^{2}}{6} * \frac{Gap \text{ of Scale Parameters}}{\text{Average Number of Alternatives in Two Travel Dimensions}} \\ R_{3} = \frac{\pi^{2}}{6} * \frac{Gap \text{ of Scale Parameters}}{\text{Number of Travel Dimensions}} \end{cases}$$
(4.6)  
$$R_{3} = \frac{\pi^{2}}{6} * \frac{Gap \text{ of Scale Parameters}}{\text{Number of Travel Dimensions}} \\ Cov \left( \varepsilon_{t,d,m}, \varepsilon_{x,y,z} \right) = \\ \text{if } var \left( \varepsilon_{t,d,m} \right) - var \left( \varepsilon_{x,y,z} \right) < R_{1}; \quad \frac{\pi^{2}}{6} \left( \theta_{1}^{2} - \theta_{1}^{2} \right) \\ \text{if } var \left( \varepsilon_{t,d,m} \right) - var \left( \varepsilon_{x,y,z} \right) < R_{2}; \\ \frac{\pi^{2}}{6} \left[ \sqrt{\alpha_{t,d,m|i}\alpha_{x,y,z|i}} \left( \theta_{1}^{2} - \theta_{1}^{2} \right) + \sqrt{\alpha_{t,d,m|j}\alpha_{x,y,z|j}} \left( \theta_{j}^{2} - \theta_{1}^{2} \right) \right] \\ \text{if } var \left( \varepsilon_{t,d,m} \right) - var \left( \varepsilon_{x,y,z} \right) < R_{3}; \\ \frac{\pi^{2}}{6} \left[ \sqrt{\alpha_{t,d,m|i}\alpha_{x,y,z|i}} \left( \theta_{1}^{2} - \theta_{-1}^{2} \right) + \sqrt{\alpha_{t,d,m|j}\alpha_{x,y,z|j}} \left( \theta_{j}^{2} - \theta_{-1}^{2} \right) + \sqrt{\alpha_{t,d,m|k}\alpha_{x,y,z|k}} \left( \theta_{k}^{2} - \theta_{-1k}^{2} \right) \right] \\ Otherwise; \qquad Zero$$

Notably, the produced overlapped nests are initial nests which are subject to modifications in the light of the initial and subsequent GNL model estimation results. An example of such changes is; elimination of one or more alternatives from a nest or shifting alternatives from one nest to another. Moreover, some suggested changes may be based on the intuitive judgments by the analyst.

Finally, in the light of the estimation results associated with the proposed GNL nesting structures, we keep imposing modifications and exchanges over nesting structures along with variations on the utility function specifications until attaining best GNL model in terms of signs and magnitudes of parameters, and overall goodness of fit.

### 4.6 Case Study

In this paper, the proposed framework is tested with an application on shopping and entertainment trips' data of Eskischir city, Turkey. These data have been collected from a household survey that was conducted in 2015 in the context of Eskischir Strategic Master Plan studies. Eskischir city (Eskişchir in Turkish) is a medium sized city in north-western Turkey with a population about 800000 (according to 2015 census data) distributed over 2700 km<sup>2</sup> area.

The considered shopping and entertainment trips' data are a part of large-scale revealed preference data which include; household-based and individual-based sociodemographics, individual's travel information and attributes of the used transportation mode(s).

In Eskischir city, most shopping and entertainment activities are concentrated in three distinct regions (Figure 4.2) which are distinguished by having a lot of retail and entertainment activities. These three regions are; ESPARK shopping centre "s", Ozdilek shopping centre "z" and Local Bazaar "l". The departure time has been categorized into three different groups that present differences in traffic conditions and availability of individuals' free times. These three times are: peak time trips "p"; 7.00 am - 9.00 am, and 4.30 pm - 6.30 pm, off-peak time trips "o"; 9.00 am - 4.30 pm, evening time trips "e"; time after 6.30 pm up to 10.00 pm. In the context of travel modes, three modes that allow access to the three destinations and available during the three departure times have been considered in our analysis as private car "c", public bus "b" and tramway "t". The total number of observations related to the determined alternatives has been found to be 529. The distribution of individuals among available alternatives of each choice subset is shown in Table 4.1.

Finally, the considered explanatory variables include: total travel time "TT" and total travel cost "TC" as alternatives' attributes, car ownership "COW", monthly income "INC", student status "SS" and age "AGE" as individuals' characteristics. Other variables related to attributes of destinations such as number of shopping and entertainment activities might have significant effects, however, unfortunately they were unavailable within the collected data.

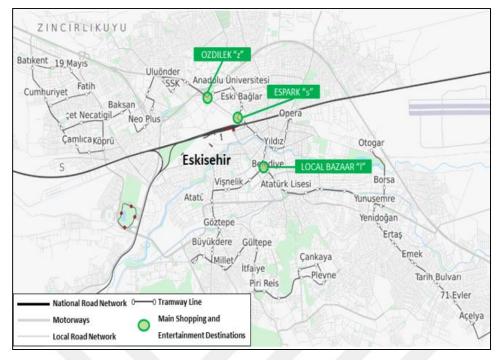


Figure 4.2 : Map of the study area.

		# of Observations	Rate (%)
	Peak (p)	104	19.66
Departure time (t)	Off-Peak (o)	277	52.36
	Evening (e)	148	27.98
	Espark (s)	184	34.78
Destination (d)	Local Bazaar (l)	203	38.37
	Ozdilek (z)	142	26.84
	Car (c)	116	21.93
Travel modes (m)	Bus (b)	98	18.53
	Tramway (tr)	315	59.55

**Table 4.1 :** Sample distributions among alternatives.

## 4.7 GNL Structure

The total number of alternatives equals 27 which includes all possible combinations of three departure times [p, o, e], three destinations [s, l, z] and three modes [c, b, t]. Equation 8 presents the general structure of the utility functions of alternatives that are formulated as linear-in-parameters (Equation 4.8).

$$V_{t,d,m} = ASC^{f} + b_{TT}^{f} * TT + b_{TC}^{f} * TC + b_{COW}^{f} * COW + b_{INC}^{f} * INC + b_{SS}^{f} * SS + b_{AGE}^{f} * AGE$$
(4.8)

In order to capture the preliminary suitable specifications of the utility function's parameters, different combinations of generic and travel dimension(s) specific parameters have been estimated through traditional MNL models. According to the estimation results, a set of specifications that lead to acceptable signs and achieve best goodness of fit is obtained as shown in equation 4.9. This equation has been used to estimate variances of error terms by using the HEV model and utilized as the initial utility function while estimating the first GNL model as well.

$$V_{t,d,m} = ASC^{m} + b_{TT}^{t} * TT + b_{TC} * TC + b_{COW}^{m} * COW + b_{INC}^{d} * INC + b_{SS}^{m} * SS + b_{AGE}^{t} * AGE$$
(4.9)

The HEV model has been estimated with 27 degenerate nests. Table 4.2 shows the estimates of error term's variance associated with each elementary alternative. In order to simply distinguish similar alternatives, the values have been sorted in ascending order.

t,d,m	$\theta_{t,d,m}$	t,d,m	$\theta_{t,d,m}$	t,d,m	$\theta_{t,d,m}$
o, l, tr	-0.13	o, l, c	7.29	p, l, b	19.76
e, s, tr	-0.05	e, s, c	7.35	e, z, b	20.97
o, s, tr	-0.05	p, s, c	7.55	e, l, b	22.83
p, l, tr	-0.05	p, z, c	7.7	o, l, b	23.21
o, z, tr	-0.03	p, l, c	7.99	e, s, b	23.41
e, z, tr	0	0, s, c	8.18	p, s, b	26.55
e, l, tr	0.02	0, Z, C	8.44	p, z, b	30.23
p, s, tr	0.02	e, z, c	9.69	o, z, b	33.41
p, z, tr	0.07	e, l, c	10.87	o, s, b	33.97

**Table 4.2 :** Variance estimates of elementary alternatives associated with HEV.

As shown in Table 4.2, obviously, elementary alternatives can be clearly distinguished based on three main categories; tramway-based alternatives, private car-based alternatives and bus-based alternatives. Another significant issue is the large gap between tramway and bus as public transportation alternatives. Surprisingly, the HEV model suggests that there is no correlation between tramway-based and bus-based alternatives at all.

In order to reach an initial GNL structure, the proposed method for different variance ranges has been applied. That is, the error term variance's gap of 34.10 has been divided by three different values to produce three different thresholds;

$$R_{1} = \frac{\text{Variances' gap}}{\text{Number of travel dimensions}} = \frac{34.10}{3} = 11.37$$

$$R_{2} = \frac{\text{Variances'Gap}}{\text{Av. number of alternatives in two travel dimensions}} = \frac{34.10}{(9+9+9)/3} = \frac{34.10}{9}$$

$$= 3.79$$

$$Variances' gap = \frac{34.10}{-1.26}$$

$$R_3 = \frac{\text{Variances gap}}{\text{Total number of alternatives}} = \frac{34.10}{27} = 1.26$$

Consequently, according to each range and the values of variances (Table 4.2) elementary alternatives have been distributed through different nests. Figure 4.3 illustrates the initial arrangement that is generated by applying the proposed method.

In the initial GNL structure, the total number of nests is 11. The first variance's range ( $R_1$ =11.37) suggests three distinct nests ( $N_1^i$ ,  $N_2^i$  and  $N_3^i$ ). For  $N_1^i$ , surprisingly, tramway and private car-based alternatives are aggregated under the same nest. Opposite to most of the previous studies that assume extreme differences between public transportation modes and private car, the proposed method identifies the existence of such an untraditional correlation. Apparently, a similarity between tramway-based and private car-based alternatives is highly unexpected. However, common unobserved attributes such as reliability of on time arrival may represent some similarities. Regarding bus-based alternatives, they are distributed among two distinct nests;  $N_2^i$  and  $N_3^i$ . While  $N_2^i$  has no specific interpretation,  $N_3^i$  (o-z-b and o-s-b) may be interpreted as a "destination ordering" pattern since it gathers two alternatives with two adjacent destinations (i.e. Ozdilek and Espark). Another interpretation that may make sense is that Ozdilek and Espark have similar a nature since both of them are considered as shopping centres rather than the Local Bazaar that mostly consists of local retails.

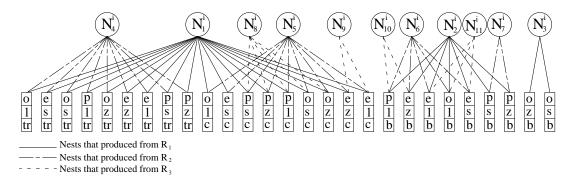


Figure 4.3 : Initial GNL structure.

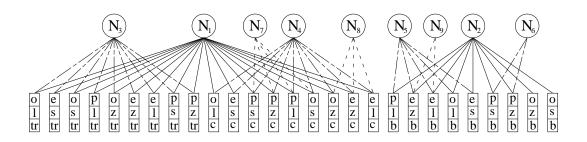
The second variance thresholds ( $R_2 = 3.79$ ) resulted in a different nesting system;  $N_4^i$  and  $N_5^i$  are tramway-based nest and private car-based nest respectively.  $N_6^i$  consists of five bus-based alternatives and  $N_7^i$  involves two alternatives (p-z-b and p-s-b). Similar to  $N_3^i$ ,  $N_7^i$  has two potential similarity sources; destinations' order and/or being shopping centres, but during another time of day (peak period).

The third range (the minimum step of 1.26) obtains other cut-offs which produce new four nests;  $N_8^i$  through  $N_{11}^i$ . Notably, no inner-correlations for tramway-nest ( $N_4^i$ ) exists. However, the nest  $N_9^i$  (e-z-c and e-l-c) suggests similarity between evening private car trips heading to Ozdilek and Local Bazaar. For  $N_{10}^i$  (p-l-b and e-z-b), correlation between bus-based trips heading to Local Bazaar and Ozdilek during different time of day is proposed. For  $N_{11}^i$  (e-l-b, o-l-b and e-s-b), on the other hand, two sources of correlation can be interpreted. The first one is the correlation between "o-l-b" and "e-l-b" which may be due to similarities between off-peak "o" and evening "e" departure times as medium and low congestion periods (temporal correlation). The second correlation is between "e-l-b" and "e-s-b" which may result from the apposition of the two destinations Espark and Local Bazaar (Figure 4.2).

The initial GNL model structure (Figure 4.3) that is generated from different variance's range method has been estimated by using N-LOGIT 6 which uses constrained maximum likelihood estimation method. In order to decrease the complexity of the model, the scale parameters have been estimated by normalizing the lower level scale parameters to unity. Moreover, for upper level, some branch scale parameters have been fixed at specific values to be able to estimate other scale parameters within the accepted range (more than unity).

Even though the estimation of the initial GNL structure led to a converged model, some parameters have been found to be unacceptable (e.g. a positive sign for travel time's parameter). At such a situation, some manipulations on the initial GNL structure have been applied until plausible estimates are attained. Such manipulations include; elimination or transferring some alternatives from one nest to another according to intuitive judgments. In order to do so in an organized manner, the imposed changes are proposed to be applied individually to each set of nests associated with each variance's range. Consequently, new GNL structures that result from the combination

of individual changes have been estimated until reaching best model. Figure 4.4 illustrates the final set of nests which attains the best results.



**Figure 4.4 :** Final GNL structure.

Finally, in order to demonstrate the dominance of the GNL model over other traditional NL approaches, along with the final GNL structure, some 3-level NL structures with different travel dimensions arrangements have been estimated as well. Moreover, some Ordered Generalized Extreme Value (OGEV) structures that consider for spatial correlation between destinations have been modelled and estimated.

## 4.8 Discussion of Estimation Results

The estimation results of the final GNL structure that provides the best results in terms of the values of parameters and overall goodness of fit are shown in Table 4.3. The final utility function specification that is used to estimate the final model is shown in Equation 4.10. Worth mentioning, income and student status variables have not resulted in statistically significant parameters at all, thus, in order to estimate certain parameters for other variables, they are eliminated from the final utility function.

$$V_{d,t,m} = ASC^{m} + b^{t}_{TT} * TT + b_{TC} * TC + b^{m}_{COW} COW + b^{t}_{AGE} AGE$$
(4.10)

In the light of estimation results, the following points can be inferred;

• The proposed GNL structure (MLL=-1245.24) accomplishes a recognizable improvement over traditional 3-level NL model (MLL=-1535.17) and over OGEV model (MLL=-1517.20) with remarkable log likelihood ratio of 543.92.

	GNL
<u>Constants</u>	
Car Specific Alternatives	-4.40 (-6.40) <sup>a</sup>
Bus Specific Alternatives	-1.80(-4.05) <sup>a</sup>
Tram Specific Alternatives	0.00 (F)
<u>Total Travel Time</u>	
Peak Specific Alternatives	-0.033(-3.04) <sup>a</sup>
Off-peak Specific Alternatives	-0.0012 (-2.90) <sup>a</sup>
Evening Specific Alternatives	0.00 (F)
Total Travel Cost (Generic-TL)	$-0.30(-5.20)^{a}$
<u>Car Ownership (F=0&amp;T=1)</u>	
Car Specific Alternatives	$2.70 (5.24)^a$
Bus Specific Alternatives	0.00 (F)
Tram Specific Alternatives (Base)	0.00 (F)
Age (Years Old)	
Peak Specific Alternatives	0.00 (F)
Off-peak Specific Alternatives	$-0.001 (2.77)^a$
Evening Specific Alternatives (Base)	0.00 (F)
Value of Time (TL/hr.)	
Peak Specific Alternatives	6.60
Off-peak Specific Alternatives	0.24
Evening Specific Alternatives	0.00
Scale Parameters (branches)	
N <sub>1</sub> (Tramway + Private Car)	2.94 (1.60) <sup>b</sup>
N <sub>2</sub> (Bus)	$7.14(1.5)^{b}$
N <sub>3</sub> (Tramway)	50 (F)
N <sub>4</sub> (Car)	1.10 (F)
N <sub>5</sub> (group of bus)	1.17 (1.11)
$N_6$ (Peak Bus-based spatial correlation)	1.13 (0.11)
$N_6$ (group of Car)	1.25 (F)
$N_8$ (Car-based spatial and temporal	
corr.)	1.00 (F)
N <sub>9</sub> (Evening Bus-Based spatial corr.)	1.05 (0.01)
Goodness of Fit	1.05 (0.01)
# of Observations	529
	48
# of parameters	-1245.24
$LL(\beta)$	-1243.24
LL(C) MLL (3 lovel NL $k=17$ )	NA 1525-17
MLL(3-level NL, k=17)	-1535.17
MLL(OGEV, k=41)	-1517.20
$-2LL(\beta vs.0)$	996.5 0.28
Adjusted $\rho^2(\beta vs.0)$	0.28
-2LL(GNL vs. OGEV, DF=7)	543.92

**Table 4.3 :** The coefficient estimates for the best GNL model.

F=Fixed Parameter, NA = Not Applicable, <sup>a</sup> Significant at 95% level, <sup>b</sup> Significant at 90% level, tstatistics in parentheses

- The model attains a relatively good over-all goodness of fit with adjusted  $\rho^2$  value of 0.28. That refers to a more prominent predictability power of the proposed GNL approach.
- Since TT parameters are specific to departure time alternatives, the model expects a significantly higher effect of TT on shopping and entertainment trips during peak periods than on trips that are performed at other times of day.
- Individuals in Eskischir city are increasingly interested in the cost of discretionary trips rather than time, especially during off-peak and evening times (i.e. times that are far away from working hours).
- Individuals in Eskischir city are willing to pay 6.60 TL (in average) to decrease an hour from their peak discretionary trip's travel time. However, this desire decreases dramatically during other times of day (off-peak and evening).
- With a travel mode-based alternative specific parameter, car ownership (COW) variable is significant for car users with a positive effect. As expected, Eskischir discretionary trips travellers have more inclination to use private car over other modes if they are car owners.
- Regarding age variable which has a departure time-based specific alternative parameter, surprisingly, elderly travellers may prefer performing their discretionary trips during peak or evening periods far away from off-peak periods.

Another important output of the proposed GNL model is the matrix of allocation parameters (Table 4.4). Reviewing relative values of allocation parameters (Table 4.4) indicates some important conclusions which we can summarize through the following points:

• For the first nest (N<sub>1</sub>), substantial unobserved similarities ( $\theta = 2.94$ ) are likely to be among tramway at peak (p, l, tr & p, z, tr) from one side and private car at evening (e, l, c & e, z, c) from the other side. Obviously, individuals in Eskisehir city are more likely to compare between performing their shopping and entertainment trips at peak periods by using tramway or waiting until late times of day to avoid traffic congestion and use their private cars. Such a behaviour, however, is associated specifically with Ozdilek and Local Bazaar. Another significant indication from this correlation is the level of service of tramway. By words, it is possible to assume that tramway has satisfactory level of service that is high enough to make decision makers perceive it similar to private cars. The opposite is correct for bus service which has no considerable correlation with any of tramway or private car. Therefore, the level of service of bus is potentially low and this leads to draw bus mode far away from private car and even from tramway. In the context of policy implications, since inhabitants of Eskisehir have such a willingness to shift their travels from car to tramway and from congested peak hours to uncongested times of day, it would be logical to implement measures such as improving the public transportation system or imposing cordon congestion pricing schemes to encourage the use of public transportation modes. Notably, such conclusions express the powerful analytical ability of the proposed GNL approach where it has the power of capturing unusual correlation patterns. These patterns are thoroughly specific, unexpected, and very difficult to be observed in the market. By words, we argue that there is no other approach as simple as the proposed one that leads to such a temporally and spatially specific deductions.

- For private car-based alternatives, along with those alternatives that are correlated with tramway alternatives (N<sub>1</sub>), all other alternatives except one strongly belong to nest N<sub>4</sub> (i.e. car-based nest) with 1.10 scale parameter. Therefore, for discretionary trips of Eskisehir city, most car-based alternatives are weakly correlated with each other. Besides, a higher correlation has been found among two specific car-based alternatives which are (p, z, c & p, l, c) where they somehow have considerable weights in nest N<sub>7</sub> (i.e. 0.11 and 0.13 respectively) with a high scale parameter (i.e. 1.25). Clearly, this represents a spatial correlation pattern between Ozdilek and Local Bazaar during peak hours for car users only. This is another important advantage of the proposed GNL model where it can precisely extract those alternatives that have some mutual dependency with actual importance (weight).
- For bus-based alternatives, rather than the traditional correlation (N<sub>2</sub>), temporal correlation can be observed between two alternatives (p, l, b & o, l, b) in nest N5. That is, individuals who do their shopping and entertainment trips in Local Bazaar by using bus mode, likely perceive some similarities for both peak and off-peak departure times.

	$N_1$	<b>N</b> <sub>3</sub>	$N_4$	$N_2$	N <sub>5</sub>	$N_6$	$N_7$	$N_8$	N9
$1 \theta$	2.9	50	1.10	7.14	1.17	1.13	1.25	1.00	1.05
o, l, tr	$0.08^{a}$	0.92 <sup>a</sup>	0	0	0	0	0	0	0
e, s, tr	0.17	0.83 <sup>a</sup>	0	0	0	0	0	0	0
o, s, tr	$0.07^{a}$	0.93 <sup>a</sup>	0	0	0	0	0	0	0
p, l, tr	$1^{a}$	0	0	0	0	0	0	0	0
o, z, tr	$0.07^{a}$	0.93 <sup>a</sup>	0	0	0	0	0	0	0
e, z, tr	0.15	0.85 <sup>b</sup>	0	0	0	0	0	0	0
e, l, tr	0.17	0.83 <sup>a</sup>	0	0	0	0	0	0	0
p, s, tr	$0.68^{a}$	0.32 <sup>a</sup>	0	0	0	0	0	0	0
p, z, tr	$0.92^{a}$	$0.08^{a}$	0	0	0	0	0	0	0
o, l, c	0	0	0.95 <sup>a</sup>	0	0	0	0.05	0	0
e, s, c	$0.0^{\mathrm{a}}$	0	$0.97^{a}$	0	0	0	0.02	0	0
p, s, c	$0.02^{a}$	0	0.95 <sup>a</sup>	0	0	0	0.03	0	0
p, z, c	$0.02^{a}$	0	$0.87^{a}$	0	0	0	0.11 <sup>a</sup>	0	0
p, l, c	$0.07^{a}$	0	0.81 <sup>a</sup>	0	0	0	0.13 <sup>a</sup>	0	0
0, s, c	0.0 <sup>a</sup>	0	0.94 <sup>a</sup>	0	0	0	0.04	0	0
0, Z, C	$0.0^{\mathrm{a}}$	0	0.12 <sup>a</sup>	0	0	0	0	0.85	0
e, z, c	0.96 <sup>a</sup>	0	0.01	0	0	0	0	0.03	0
e, l, c	$0.98^{a}$	0	0	0	0	0	0	0.02	0
p, l, b	0	0	0	0.51 <sup>a</sup>	0.49	0	0	0	0
e, z, b	0	0	0	0.98 <sup>a</sup>	0	0	0	0	0.02
e, l, b	0	0	0	0.94 <sup>a</sup>	0.0	0	0	0	0.05
o, l, b	0	0	0	0.13 <sup>a</sup>	0.87	0	0	0	0
e, s, b	0	0	0	0.99 <sup>a</sup>	0	0	0	0	0
p, s, b	0	0	0	0.61 <sup>a</sup>	0	0.39	0	0	0
p, z, b	0	0	0	0.96 <sup>a</sup>	0	0.04	0	0	0
o, z, b	0	0	0	1 <sup>a</sup>	0	0	0	0	0
o, s, b	0	0	1	0	0	0	0	0	0

**Table 4.4 :** Matrix of allocation parameters for the estimated GNL model.

<sup>a</sup> Significant at 95% level

#### **4.9** Conclusions

In the light of estimation results, it is possible to argue that the proposed GNL approach has distinct improvements over all traditional NL approaches. Its simplicity along with the incomparable flexibility in representing a lot of correlation patterns within and among different travel dimensions under a unified model qualify it to be prominent. The proposed GNL model can provide very detailed analyses about the interrelationships associated with various departure times, travel modes and discretionary destinations where other "simple" models cannot. That leads to more certain, specific, efficient and precise policy decisions. For example, in the case study, while heading to specific discretionary destinations, the model succeeds to discover the unanticipated correlation between using private car at peak periods from one side and public transportation at evening periods from the other. Such a multi-dimensional dependency can provide decision makers with extremely useful indicators prior to the application of different policy implications.

The advantages associated with the proposed GNL approach perhaps qualify it to be a peer to the well-known traditional four-step models if applied on discretionary trips in small and medium-scale planning issues (small or medium sized cities) with limited number of alternatives within travel dimensions. The proposal of using GNL approach to model departure time, destination and travel mode choices under a unified framework is considered as a milestone towards developing joint models that can efficiently and accurately replace the traditional four-step models and keep on degrees of easiness to advocate engineers and policy makers rely more on them. It represents a time of day-based trip-end distribution model that can reproduce extremely more accurate origin-destination matrices dependent on time of day. Moreover, unlike traditional four-step models, parameter estimates produced from the GNL model can provide significant indications which precisely reflect the real behaviour of individuals. That can enormously help policy makers to reach to a solid perception about the effects of applying some strategies to manage demands through different times of day and towards different destinations.

Finally, when applied on the case study, the proposed methodology (Figure 4.1) has shown enough flexibility during its different stages; the estimation of a proper utility function, producing data-based GNL nesting structures and attaining the best GNL model. That result supports the applicability of the proposed methodology when applied on other cities that have similar socio-demographic and size conditions. Moreover, more complicated choice situations that have higher number of alternatives may be readily handled in future researches through computerizing such methodology under a sophisticated computer routine or by using more advanced statistical techniques.



## 5. CONCLUSIONS AND RECOMMENDATIONS

## **5.1 General Conclusions**

In the light of estimation results, some conclusions found common between all proposed models. These conclusions can be summarized as follows:

- While performing shopping and entertainment trips, individuals jointly decide on "at which departure time", "to which destination" and "by which mode" rather than separately. This could be discovered by examining the existence of statistical correlations among those three travel dimensions. This assumption has been proved in Eskischir city where all proposed models that represent different hierarchal decisions with different correlation structures have been found statistically significant compared with standard MNL models.
- For any proposed nesting structure of departure time, destination and travel mode, in order to attain statistically accepted models in terms of log likelihood value at convergence, overall goodness of fit and other tests related to significance and sign of coefficient estimates, some specifications which restrict parameters of utility function's variables with one or more travel dimension had to be assumed and examined. For example, in our case study, most of the qualified models have been found to be associated with the following specifications; (1) parameter of total travel time to be specific to departure time, (2) parameter of total cost to be generic, (3) car ownership to be specific to travel mode, (4) income to be specific to destination or mode, (5) student status to be specific to mode and (6) age specific to be departure time. Notably, such specifications reflect direct implications for individuals' behaviour while performing these types of trips and lead to simple and intuitive interpretations of coefficient estimates.

Neglecting the potential correlation among alternatives of departure time, destination and travel mode leads to inaccurate estimates which results finally in incorrect and improper policy decisions. For example, in the performed analyses, neglecting correlation in MNL model has led to totally different estimates of VOT than those estimated from the more advanced models (OGEV and GNL). That may be translated to insufficient and unsuccessful monetary policies by decision makers in transportation sector. The same conclusion can be clearly demonstrated through reviewing the results associated with other studies which did not consider correlation between different travel dimensions. For example, the model proposed by Bowman and Ben-Akiva (2001) has connected departure times from one side with the combinations of destinations and travel modes from the other without accounting for associated correlations. The estimation results of the model's prototype that was introduced for Boston are found to have some faults. For instance, unrealistic estimates for VOT have been obtained.

- The predictability of a proposed model increases as the considered heterogeneity levels increases. That could be observed in our case study where more advanced models have better goodness of fit (rho square) when compared with simpler models.
- The coefficient estimates of total travel time (specific to departure time) are statistically significant and have negative sign for all proposed models. The magnitudes of parameters guided to conclude that, when performing shopping and entertainment trips, individuals perceive much more concern to travel time at peak periods than off-peak and evening trips.
- As a generic parameter, total travel cost rationally occurs to have negative sign with magnitudes that are statistically significant at 90% level of significance for all models. Yet, in most models, relative to the parameter of total travel time, individuals in Eskisehir city may give more importance to cost than time while performing shopping and entertainment trips.
- Regarding VOT, in all models, individuals in Eskisehir city have more willingness to pay to decrease travel time at peak hour trips than off-peak times. From another hand, the large gap observed among VOT related to traditional and more advanced models reveals the extreme effect of introducing multidimensional correlation among elementary alternatives of departure time, destination and travel mode choices.

- The value of car ownership parameter estimates (specific to travel mode) show an inclination towards performing shopping and entertainment trips by using private car rather than public transportation if the individual owns car(s).
- The income parameters (specific to destination) are significant in most models and suggest that individuals with higher monthly income are more likely to prefer doing shopping activities in shopping malls rather than local retails.
- For student status variable, significant and negative signed alternative-specific coefficients for private car mode imply that, as expected, students are more likely to use public transportation over private car while heading to shopping and entertainment destinations.
- The estimates of age variable parameter are significantly different than zero and have positive signs in most models (all except GNL model). Specific to departure time, getting older decreases the probability of performing shopping and entertainment trips at peak periods and evening as well.
- Finally, a set of data that is suitable to estimate joint departure time, destination and travel mode discrete choice model shall include; total travel time and total travel cost as attributes of alternatives, car ownership, age and monthly income as individuals' characteristics. Moreover, other independent variables related to the attributes of destinations (which were not available in our data set) may increase the predictive power of the model such as; size of traffic analysis zones (e.g. area), area of different land-uses, opening and closing hours, availability of special services, number of activities.

#### 5.2 Model Specific Conclusions

Besides to the general findings, other crucial conclusions have been found related to specific models which can be summarized as follows:

## 5.2.1 Three-level NL model

When representing departure time, destination and travel mode through three-level NL model, the existence of different nesting structures with very near overall goodness of fit indicates a high portion of heterogeneity in the sample. Such various correlations can be considered only with more advanced choice models such as GNL model or Mixed Logit approach. This conclusion expresses the importance of the proposed GNL

model where it can exhibit various overlapped correlation patterns with fewer burdens in the estimation process.

## 5.2.2 OGEV model

In the proposed OGEV model, the superiority of hybrid ordering pattern (Locationbased and Travel Time-based) implies that, for discretionary trips, individuals are more likely to decide on destination firstly with high correlation between destinations that have similar travel times. Consequently, they properly capture the departure time and travel mode. Therefore, in order to mitigate congestion that is produced from such type of trips, transportation planners could suggest spatial-based measures rather than temporal-based ones.

Moreover, the proposed hybrid ordering pattern provides detailed analyses (microanalyses) about the spatial correlation associated with various, departure times, and travel modes where traditional four-step model cannot. For instance, in Eskisehir city, while performing shopping and entertainment trips, public transportation users have been found acquiring common unobserved utility for Ozdilek and Local Bazaar destinations. On the other hand, private car users perceive similarities for Ozdilek and Espark destinations. Thus, policies that encourage the using of public transportation will lead to entirely different results than policies that restrict the using of private car.

## 5.2.3 GNL model

The previous proposed models have proved that our assumption about the existence of cross-correlation between various travel dimensions is correct. That is, in addition to the correlation between alternatives within the same travel dimension (e.g. within destinations), there are other correlation patterns between travel dimensions (e.g. between travel modes and destinations). That means the existence of overlapped and crossed correlations within different alternatives. When tried to express such a complicated dependency structure through traditional NL models, it seems that two and three-level NL models are not adequate whereas multi-level NL structures (more than three) are too complicated to be estimated efficiently. Therefore, another approach which gathers both estimation simplicity and flexibility in introducing various potential correlation patterns is required. In this dissertation, it is argued that, a Generalized Nested Logit model (GNL) is proper for such conditions.

The proposed GNL methodology has shown distinct improvements over all other proposed models. It collects between simplicity of application and high flexibility in representing multi-dimensional heterogeneity under an integrated model. The model attains a relatively good over-all goodness of fit with adjusted  $\rho^2$  value of 0.28 which lead to a more prominent predictability power.

The proposed GNL model has a powerful analytical ability where it has the power of modelling unusual heterogeneity patterns. These patterns are very particular, unexpected, and very rare to be detected. Therefore, more solid, specific, effective and accurate policy decisions will be obtained. For instance, in the case study, the GNL model has revealed decision makers' inclination towards trading-off performing their shopping and entertainment trips at specific time by using specific travel mode or travelling through another time of day to avoid using this travel mode. Such a behaviour, however, has been determined for specific discretionary destinations.

From another hand, when applied for medium-scale planning issues (e.g. 30 elementary alternatives), the proposed GNL methodology offers a more accurate alternative to the well-known traditional four-step model especially when more detailed and specific analyses (micro-analyses) are required. That is, it provides a time of day-based trip-end distribution model that can produce extremely more accurate origin-destination matrices dependent on time of day. The proposed GNL model successfully overcomes the limitations of traditional four-step model associated with fixed sequence of steps, independent choices, ignorance of decision maker characteristics and shortages in representing actual behaviour of travellers.

Moreover, unlike traditional four-step models, parameter estimates produced from the GNL model can provide significant indications which precisely reflect the real behaviour of individuals. That can enormously help policy makers to reach to a solid perception about the effects of applying some strategies to manage demand through different times of day and toward different destinations. For example, the developed aggregate four-step model that was calibrated for Eskisehir city under the strategic master plan project in 2015 has estimated an average VOT for the whole city independent of time of day and destination that is 15.81 TL/hr. That means, a policy maker that aim to decide on a specific monetary implication will build his/her decision only on that average value (one supply demand curve) regardless of the applied times and places. However, the proposed GNL model provides VOT estimates dependent on

one or more travel dimensions (multiple supply demand curves). That is, the policy maker can obtain departure time, destination and or travel mode specific VOT estimates through formulating different utility function specifications for time and cost independent variables. Therefore, different policy implications can be applied at different times of day and for different destinations.

Overall, the interpretations of parameter estimates from the proposed GNL model (utility function estimates, allocation parameters and scale parameters) can provide decision makers with very specific recommendations such as; VOT based on travel mode, time of day and destination which can be used to estimate supply-demand functions dependent on time of day and destination, effective locations and times to apply congestion pricing and cordon pricing, best locations to apply different public transportation development measures, optimal locations and times to apply private car restriction measures. Moreover, the value of cross-elasticity between any pairs of alternatives (i.e. simulation) will provide policy makers with the specific compensation between times, destinations and travel modes if specific change in an independent variable is imposed (e.g. increasing travel cost).

The proposed GNL model contributes to the literature of transportation demand modelling that leads to a better understanding of the influences of different temporal and spatial factors on individuals' travel choices. The need for such models increases after the pandemic of COVID-19 that invaded the world in 2020 which had its own influences on the future transportation planning studies. By words, policy makers have directed their interests toward newly emergency transportation policies that aim to distribute travels over wider time and space spans in accordance with precautionary and preventive measures to counteract Corona virus or any other similar future virus attacks. Therefore, models like our proposed one that consistently, accurately and simply represent dependency between departure time, destination and travel mode are very important to be formulated.

There are some limitations associated with the proposed framework. The first limitation comes out when the number of interacted alternatives increases in large sized cities that have many number of discretionary destinations. That leads to more complicated cross-nested structure and makes the estimation process harder. However, future researches can direct their interest to overcome such a limitation through modern statistical means. For instance, a developed Choice Set Formation technique that is compatible with GNL approach can be a very useful solution (see Hassan et al, 2017). Another important point which is neglected in the proposed GNL methodology and may be considered in future researches is adopting multi-utility functions under the overall function to explicitly represent variables specific to each travel dimension. This approach will be useful in imposing destination specific variables such as size of traffic analysis zones, area of different land-uses, opening and closing hours, availability of special services, number of activities, etc.

Finally, despite the applicability of the proposed methodology is restricted to limited number of alternatives which makes it more proper for small and medium planning scopes (small and medium sized cities), it can surely be considered as a significant milestone toward developing full and integrated models. These models can efficiently and accurately provide more detailed and specific micro-policy analyses where traditional four-step model cannot while keeping on degrees of easiness to advocate engineers and policy makers rely much more on them. That can be achieved through future studies that may develop the proposed GNL methodology and benefit from the revolutionary developments in computers and statistical software to produce more applicable future prediction tools.



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