Modelling preference heterogeneity for theatre tickets: a discrete choice modelling approach on Royal Danish Theatre booking data *

Andrea Baldin†

Trine Bille‡

Abstract

This paper analyzes the behavioural choice for theatre tickets using a a rich dataset for 2010-2013 from the sale system of the Royal Danish National Theatre. A consumer who decides to attend a theater production faces multiple sources of price variation that depends on: socio-economic characteristics, quality of the seat, day of the performance and timing of purchase. Except for the first case, factors of price differentiation involves a choice by the consumer among different ticket alternatives. Two modelling approaches, namely multinomial logit (with socio-demographic characteristics) and latent class are proposed in order to model ticket purchase behaviour. These models allow us explicitly to take into account consumers' preference heterogeneity with respect to the attributes associated to each ticket alternative In addition, the distribution of the willingness-to-pay (WTP) of choice attributes is estimated. Understanding theatre-goers' choice behaviour and WTP for the quality of seat and the day of performance is important to policy makers and theatre managers in adopting different pricing and marketing strategies.

Keywords Theatre demand - Discrete choice models - Price discrimination - Willingness to pay

---

*PLEASE DO NOT CIRCULATE OR CITE WITHOUT PERMISSION

†Ph.D. Fellow, Department of Management, Ca' Foscari University of Venice, Cannaregio 873, 30121 Venice, Italy
E-mail: andrea.baldin@unive.it

‡Associate Professor, Ph.D., Department of Management, Politics and Philosophy, Copenhagen Business School, Porcelnshaven 18B, 3.floor, 2000 Frederiksberg, Denmark
E-mail: tbi.mpp@cbs.dk

1 Introduction

During the last years revenue management and price discrimination techniques are playing an increasing role in the performing arts sector. Evidence shows how theatres can charge different prices for the same production. This practice is driven, on the one hand, by the social duty consisting in allowing consumer segments, who are supposed to be less able to pay, to attend a theatrical production; on the other hand by the possibility to extract part of the consumer's surplus. An example of the first situation is exhibited in discount tickets offered to certain social categories (students, youth, senior citizens...). In the latter case, the theatre incentives the consumers to discriminate among themselves offering a schedule of different prices according to the quality of the seat. Doing so, each consumers will choose the seat location in the venue according to his reservation price and his preference. Another form of price discrimination is made explicit through a variation in prices, both in the full and in the discount ticket price, according to the day of the performance: for example, a ticket for Saturday night performance is usually more expensive than a ticket for a weekday performance. This kind of differentiation refers to the peak load pricing issue that takes into account the capacity constraint of the theatre, increasing the price when the demand is high and decreasing when it is low.

The pricing strategies described above are perfectly coherent with the different objectives that are pursued by a non-profit performing arts organization, as described by Hansmann [1981]: in enabling people with lower willingness to pay to attend a performance, the theatre satisfies the objective to maximize the attendance; while the appropriation of consumers' surplus fulfills the budget goal, generating excess revenue to subsidize activities that can be less lucrative but artistically important (quality goal). After all, as Rosen and Rosenfield [1997] point out, price discrimination is observed in activities, as the performing arts, where the marginal costs of providing the service to one more customer is smaller than the average cost: the additional cost to fill one more seat in a theatre is in fact fairly small

As the attendee can choose among different ticket alternatives, it is crucial to understand their behaviour in order to support pricing strategies.Based on a unique sale system dataset from the Royal Danish National Theatre during the period 2010/11 to 2012/13, we aim to analyze which attributes affect the choice of theatre ticket. Indeed, the Royal Danish Theatre provides a good example of discriminatory pricing. Taking advantage of this rich dataset, this study adopts revelead preference (RP) design approach (i.e choice based on actual market behaviour), as opposed to stated preference approach (i.e choice based under hypothetical scenarios). Both approaches are founded in the theory of consumer demand postulated by Lancaster [1966] and present advantages as well as disadvantages: RP needs a large amount of data to be implemented, in order to encompass enough variation in the level of attributes, while SP is more flexible in the design of data, providing new non-existing alternatives in the hypothetical scenarios subjected to the respondents. However, the main drawback of SP is the risk of response bias under experimental conditions that, according to Carrier [2006], seems to be high for pricing applications. Given the characteristics, in terms of details and wideness, of our dataset we adopt RP perspective in this study.

From a methodological point of view, we compare two different approaches to discrete choice analysis: Multinomial logit (MNL) with socio-demographic specification, and Latent Class Models (LCM). While the MNL model includes interaction terms with socio-demographic terms in order to account for heterogeneous preference, the LCM approach allows the parameters of the utility function to vary across agents according to a probabilistic discrete distribution. As Green and Hensher [2003] point out, LCM is supported by strong statistical foundations and has a clear interpretation as it identifies different cluster of customers each of which is characterized by specific value of the parameters. Therefore LCM is appealing from both marketing and policy perspective as it distinguish, along behavioural variables, distinct classes of customers characterized by different price sensibility and willingness to pay. Moreover, LCM overcomes the Indipendence of Irrilevant Alternatives (IIA) restriction of MNL, according to which the odds of choose one alternative over another alternative is not altered by the addition of a new alternative.

The assumption of heterogeneity seems to be realistic in the theatre sector: empirical studies on demand for performing arts has shown ambiguous values of price elasticity, in some cases even a positive elasticity configuring the theatrical experiencece as a Veblen good [Laamanen, 2013]. Indeed, many of this studies use aggregated data and the average price (revenue divided by attendance) in estimating price elasticity. Studies that has accounted the different source of price variation (and our dataset allow us to do) results in the estimation of different level of price elasticity. Hence, literature confirms how there is heterogeneity among customers in the price sensitivity.

This paper aims to investigate this preference heterogeneity analyzing the choice of ticket theatre. Compared to previous research on theatre demand, we consider all the wide range of price faced by customers. For this aim, we adopt a discrete choice modelling approach and estimate the different willingness to pay for the choice attributes. This approach is widely used in the transportation industries (airline and railway in particular); to the best of our knowledge, Willis and Snowball [2009] and Grisolia and Willis [2011a-b, 2012] are the only ones who apply discrete choice model in the performing arts sector. They have investigated preference for the different attributes of theatrical production (as venue, repertory classification, word of mouth, type of play, author and review). In addition to their work, we consider also the attributes that are sources of price differentiation: seat category, attributes of the different performances for the same production (day, premiere or not), consumer category. This is the main contribution of this study, providing a new segmentation of the theatre demand. This may have important implications as the identification of market segments with different willingness-to-pay for a theatrical attribute, is relevant to policy makers and theatre managers in adopting different pricing and marketing strategies.

The structure of the paper can be outlined as follows: Section 2 reviews the literature about demand for the performing arts and price discrimination in the theatre sector; Section 3 offers a description of the Royal Danish Theatre and its price discrimination policy; Section 4 describes the models that will be implemented while Section 5 presents the dataset and the variables used. Section 6 shows the final result. FInally Section 7 provides some conclusions and implications of our research.

2 Literature Review

This study follows mainly two streams of literature. The first relates to the determinants of demand for performing arts. Many studies have aimed to identify the elasticity with respect to price and/or income. This topic is so widely analyzed that we refer to Seaman [2006] for a comprehensive review. In addition to price, other variables has been included as determinants of performing arts attendance, as the price of substitutes [Colbert *et.al*, 1998; Zieba 2009 among others], quality indicators [Throsby, 1990; Urrutiaguer, 2002 among others], type of play [Abbè-Decarroux, 1994; Corning and Levi, 2002 among others] and socio-economic variables as education level and availability of time [Werck and Heyndels, 2007; Swanson *et.al*, 2008 among others].

The papers most related to ours are those that infer consumer heterogeneity through attributes which underlie price discrimination. This implies the adoption of disaggregated data for the price measure and demand. One of the classic segmentation is based on whether the consumer is a subscriber or not. Felton [1994] analyzes the demand of 25 large US orchestra and estimates two different regressions: the first considers only subscribers while the second one include also the single ticket holders. The author obtains a lower price elasticity for the subscribers (-0.24) compared to the total attendance price elasticity (-0.85). Colbert *et al.* [1998] through a survey conducted among the audience of seven Canadian theatre, identifyies two segments of consumers in both the subscribers and non-subscribers group according to their sensitivity to price: those who show a high price elasticity are rich in time and poor in money; the opposite regarding the other group. Abbè-Decarroux [1994] estimates demand for a Geneva theatre company, distinguishing two kind of tickets: full-price tickets and reduced price-ticket for students, senior and unemployed. As expected, for the latter consumer group is found a higher price elasticity (-2.45) while the price coefficient for the consumers who buy a full-price ticket is not statistically significant, denoting a price inelasticity. Schimmelpfennig's [1997] paper employ a non-parametric linear regression analysis to the demand for the Royal Ballet Summer Season, a special event organized by the Royal Opera House Convent Garden. The main characteristic of this paper is that it focuses on the individual seat categories. Surprisingly, for both the productions examined, the Orchestra Stalls shows a higher price elasticity than the cheapest seat category denoted as Rear Amphitheater, that is supposed to serve low-income consumers.

Corning and Levy [2002], instead of estimating different equations for subscribers and single-ticket holders, decided to model the effect of number of subscribers and price of

subscription on the demand for single tickets, including them as explanatory variables in the single full-priced tickets equation. An interesting result is that the subscription sales has a weak effect on the demand of single tickets, hence configuring two different segments with little overlap . A remarkable characteristic of their work is the inclusion of variables related to the time of performance (e.g matinee, evening, preview..),that are shown to be highly correlated with scheduled price, and to seasonality effects (monthly dummy variables): final results indicate a significant positive effect of evening and week-end performances.
Laamanen [2013] uses 8 years sales system data of the Finnish National Opera to estimate demand for opera for both premier season and reprises. For the former the price elasticity is fairly small (-0.69) while the demand for reprises is highly elastic (-3.99). What distinguishes this paper from the previous one is, not only the estimation method based on censored quantile regression that allow to take into account the capacity constraint, but also the disaggregation of ticket sales by area of seating and price category. Doing so, the author avoid bias estimation of price elasticity that results when the average price ticket and aggregated data are used in the demand estimation.
From a methodological perspective, discrete choice models has already been used in the cultural economics domain: in particular Latent class models was employed to explain the heterogeneity in culture consumption [Chan and Goldthorpe, 2005] and cinema attendance [Fernandez-Blanco *et al.*, 2009]. In the theatre sector, discrete choice models has been used in order to assess preference for theatrical attributes (as venue, repertory classification, word of mouth, type of play, author and review) and to estimate the willingness to pay for each attribute. In particular Willis and Snowball [2009] and Grisolia and Willis [2011a, 2011 b] use a Stated Preference discrete choice experiment using MNL and Mixed Logit models; while Grisolia and Willis [2012] employ a LCM that allows to segment audience according to their preferences for attributes of theatrical productions (repertory classification, type of play, author, review...). Their results suggest a heterogeneous effect of such attributes on the consumer choice.
The second stream of literature relates to the application of Revenue Management(RM) and price discrimination techniques in the performing arts organizations. As RM is an area of research that finds widely application in airline and hotel industry, there is very little empirical research that has been done in the cultural sector. Most of it has focused on the price discrimination practice implemented by theatres. Huntington [1993] considers a variant of the hedonic price model to describe price differentiation by seat. This model implies that, if there are observable differences between seats, a price discrimination policy can be adopted. Moreover the author shows that the price discrimination policy leads to a greater profit than the unique price policy. Rosen and Rosenfield [1997] describe, from a theoretical perspective, a model of price discrimination focusing on the issue on how the theatre should sort seats in categories and how should be priced, in order to maximize revenue. In the model proposed, the theatres has two qualities of seat (high and low) and the seller knows the intensity of the aggregate demand for each quality and its distribution.

Leslie's [2004] paper is considered one of the most important research on pricing strategies in the performing arts field. The author has analyzed the price discrimination policy for the Broadway show *Seven Guitars* estimating a structural econometric model based on the individual consumer behaviour. Tereyagoglu *et al.* [2012] employs a competing hazard framework to model the ticket sales, where the customers race against each other for the same ticket. The aim of their work is to analyze how pricing and discount actions over time affect the timing of customers purchase as well as the propensity to purchase a ticket by different categories of customers (subscribers and occasional buyers).
This review of literature highlights the need to use disaggregated data over price category and performance, in order to analyse consumer behaviour towards the price discrimination policy. Given the structure of our data set, a discrete choice model that account for heterogeneous preference in a RP setting seems to be the most suitable approach.

3 The price discrimination policy of the Royal Danish Theatre

The Royal Danish Theatre was founded in 1748 and is the Danish national theatre. It has three main Stages in Copenhagen. *The Old Stage* from 1874, a new *Royal Opera House* from 2005 and a new *Royal Playhouse* from 2008. The *Opera House* and the *Playhouse* has a main stage and smaller stages for experimental productions. It is one of the few theatres in the world offering both opera, ballet and theatre performances as well as classical concerts. Before the two new houses were build, the *Old Stages* offered both opera, ballet and theatre performances. Now The *Old Stage* is the house, where ballet is performed. The price discrimination policy by seat tier has been refined in the last years. In 2010 *The Opera* and *The Old Stage* offered 5 different price zone, while now the price variation involved 8 different seat categories. A different policy is adopted concerning *The New playhouse* where the discrimination by quality of seat (up to the maximum of 5 price zones in the theatre) are applied only to few production [1]
Besides price zones, each ticket sold is characterized by the price type which is connected to the characteristics of the buyers that affect the price charged. In this works we have excluded some price type, such as the categories for which the ticket is free (press, sponsor, guests, attendant for disable, employees) and group sales. Moreover we have excluded performances with a flat price, i.e the price is fixed regardless of the seat choice[2], rush tickets (discounted by 50%) and those tickets that are discouted as the result of an advertising campaign. The logic behinds this selection lies in the fact that these type of tickets either do not show a trade-off between price and seat tier, or do not gives the opportunity to the customer of a complete choice of the seat category and/or day of the performance. Table 1 shows the price types considered in our model. Apart from the standard ticket,

[1] Clearly, our sample of productions include only those in which price discrimination by seat quality is applied

[2] E.g. such performances as the open dress rehearsals and the previews before the opening night

	Price type	Price type group	Price type category	Discount in %
1	Standard	Standard	Standard	0
2	Youth[a]/Student	Social awareness	Discount	50
3	Senior citizen[b]	Social awareness	Discount	50
4	Theater card (Loyalty card)	Loyalty	Discount	10
5	Theater discount	Loyalty	Discount	20
6	Subscription choose your own - youth	Subscription choose your own	Subscription	60
7	Subscription Fixed - youth / Student	Subscription fixed	Subscription	65
8	Subscription choose your own	Subscription choose your own	Subscription	10
9	Subscription Fixed	Subscription fixed	Subscription	15

[a] Under 25 years [b] Only for retirees

Table 1: Price type used by Royal Danish Theatre

price types can be roughly divided in two category: discount and subscription. Discounts can be applied to young people, student and senior citizen for social awareness purposes and also to those who sign up for a loyalty program. In the latter case, customers buy a loyalty card which entitles them some benefits, including a discount on the ticket price of the theatre performance.

Royal Danish Theatre applies two kind of subscriptions: a fixed subscription, in which the bundle of productions included is predetermined by the theatre, and a subscription "choose your own" that allows the customer the possibility to choose the productions they want to see. In the latter case, subscribers commit to purchase a pre-set quantities of tickets and, during the season, they freely choose the content of their bundle. In general terms, subscribers benefit from a discount with respect to the standard ticket price: this is an example of the second degree price discrimination, according to which the unit price varies depending on the quantity demanded.

Figure 1 shows how the sales of tickets are distributed among the different price types.

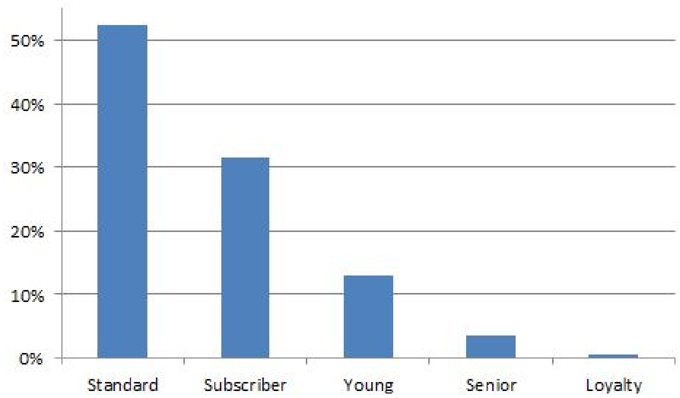

Figure 1: Percentage of ticket sold by price type

The low percentage of *Senior* ticket is apparently surprising. Indeed, many senior customers are subscribers: thus it is not convenient for the theatre to offer a discount for senior customers for all the productions. Senior customers are entitled to a discount of 50% only for some productions decided by the theatre management. Given this, in our

model these senior customers are rapresentative of retirees customers who occasionaly attend the theatre.
After the decision to attend a production, the consumer decides the day and the seat quality. Each combination of day/seat has a different price that can be discounted according to Table 1.

4 Methodology

We consider a situation in which the consumer, after deciding which production to attend, evaluate a finite number of ticket alternatives each of which differ by the quality of seat and day of performance (premiere, saturday evening and so on)[3]. Such combination of seat and day of performance constitute the choice set C. According to the random utility theory, the utility of alternative j received by the consumer i is given by:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

The utility is partitioned in two components: the deterministic (or systematic) utility V_{ij} that is observed by the analyst, and a residual term ϵ_{ij} that includes unobserved effects. It is assumed that the deterministic part is a linear function of the observed attributes of each alternatives, so that the utility function of alternative j can be written as:

$$U_{ij} = \beta' X_{ij} + \epsilon_{ij} \tag{2}$$

where X_{ij} is a vector of values representing attributes of the alternative j and β' is a vector of the corresponding parameters to be estimated.
Hence, the probability that the individual i choose the alternative j is given by:

$$P_{ij} = P(V_{ij} + \epsilon_{ij} \geq V_{ik} + \epsilon_{ik} \quad \forall k \neq j) = P((V_{ij} - V_{ik}) + \epsilon_{ij} \geq \epsilon_{ik}) \quad k \neq j, \forall k \in C \tag{3}$$

We impose that the error are independent, and identically random variables distributed according to a Gumbel distribution. As the difference between two Gumbel variables is a logit random variable, the expression (3) takes the following form [McFadden, 1974]:

$$P_{ij} = \frac{exp(\beta' X_j)}{\sum_{k \in C} exp(\beta' X_k)} \tag{4}$$

The coefficient of (4) are estimated by maximizing the likelihood function. The contribu-

[3]Some studies in the transportation industry would suggest to consider the ticket decision as a decision made at the lower nest, while the mode decision is made at the upper nest [Whelan *et al.*, 2008]. Similarly, we could consider the decision on which production to attend as an upper nest decision. This kind of decision is the approach adopted by Grisolia and Willis [2011a-b, 2012]. However, this study is based on confirmed booking data so we assume that the production decision has already been made

tion to the likelihood for the individual i is given by:

$$P_i = \prod_{j \in C} P_{ij}^{y_{ij}} \tag{5}$$

where y_{ij} is a dummy variable equal to one if individual i made choice j, 0 otherwise. Taking the log of both sides we obtain:

$$lnP_i = \sum_{j \in C} y_{ij} lnP_{ij} \tag{6}$$

that leads to the overall log-likelihood function for the sample:

$$lnL(\beta) = \sum_{i=1}^{n} \left(\sum_{j \in C} y_{ij} lnP_{ij} \right) \tag{7}$$

In the conditional logit and MNL models, parameters β are assumed to be fixed among the population: this implies the same preference structure among customers as the marginal utility of the attributes are the same in the population of theatre-goers. This assumption seems unrealistic in the performing art sector. Heterogeneity can be efficiently addressed including both socio-demographic characteristics and choice situation variables. Indeed, as discrete choice models works on the difference in utility, these variables that do not varies over alternative can enter in the model in two ways. First, interacting them with attributes of the alternative; second, including them in $J-1$ alternatives. Doing so, these variables are able to affect the difference in utility.

In our application, we include as consumers' characteristics variables the information derived by the type of ticket sold in terms of discount that identify consumer types (student, senior, subscriber and so on);the period in which the ticket has been sold and whether the customer is a foreigner or not. Moreover, also the characteristics of the production are used as variables to accomodate heterogenetiy among the population. Such variables indeed do not vary across alternatives and are supposed to reflect consumers' characteristics. Different productions, in terms of genre, newness, highbrowness and lowbrownes attract different consumers in terms of social class [see Sinatas and Alvarez, 2005] and consequently it is likely to affect the marginal utility of ticket attributes.

In our dataset we have customers - as the subscribers - who repeat the choice more than once. Given the assumption of i.i.d of the error component, it is not possible in MNL to account for correlation within individual preferences. However, we attempt to overcome this restriction including these variables related to the production: indeed, even if these variables are choice invariant, they can vary across the repeated chocies made by the same individuals. In such a way we consider the choices made by the same customers as choice made by different individuals that differ each other by the values of the production variables.

Another way to incorporate preference heterogeneity is the latent class model (LCM). The logic underlying LCM is that the population can be sorted in S classes, such that individuals within the same class have homogeneous preference. Therefore, each parameters β takes s different values with corresponding probabilities. The probability of an alternative j to be chosen by a randomly chosen individual n is given by:

$$P_{ij} = \sum_{s=1}^{S} P_{ij|s} \cdot M_i(s) \tag{8}$$

where $M_i(s)$ is the probability that the individual i belongs to class s. In other terms, (5) is a sort of weighted average of different MNL models (as many as the number of classes), with the weights represented by the size of each class in the population. The analysist doesn't know to which class a individual belong, however the likelihood of the individuals belonging to a class can be inferred through a probabilistic assignment process called membership function, that includes individual-specific variables. A multinomial logit model specification is a convenient form for the class membership model. Hence, the probability of individual i to belong to the latent class s is given by:

$$P_{is} = \frac{exp(\eta_s' Z_i)}{\sum_{s=1}^{S} exp(\eta_s' Z_i)} \quad \forall s \neq S; \quad \eta_S = 0 \tag{9}$$

where Z_i is a vector of the values of the individual-specific variable for the individual i while θ_s is the corresponding parameter for class s to be estimated. Notice that for one latent class (the last one, S) the parameters are normalized to 0 to secure identification of the model [Greene, 2003].

Including the membership function in (5) we obtain the probability of choosing alternative j by individual i:

$$P_{ij} = \sum_{S=1}^{s} \left[\frac{exp(\eta_s' Z_i)}{\sum_{s=1}^{S} exp(\eta_s' Z_i)} \right] \cdot \left[\frac{exp(\beta_s' X_j)}{exp(\sum_{k \in C} \beta_s' X_k)} \right] \tag{10}$$

A feature of the LCM is noteworthy: with the presence of the membership function, he probability to select one alternative over another contains arguments that include the systematic utilities of the other alternatives available. Hence, the IIA assumption can be relaxed [Boxall and Adamowicz, 2002]. The parameters of the LCM are estimated maximizing the overall log-likelihood function for the sample:

$$lnL(\beta, \eta) = \sum_{i=1}^{N} ln \left[\sum_{s=1}^{S} M_{is} \prod_{j \in C} P_{i|s}^{y_{ij}} \right] \tag{11}$$

In estimating (11), the number of classes S is taken as given. Its determination is usually done through statistical criterion, such as BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion) which are considered as a guide to determine the number of classes [among others see Kamakura and Russel, 1989; Swait, 1994; Roeder et al., 1999;

Wedel and kamakura, 2000]. These tests are calculated as follow:

$$AIC = -2LL + 2K$$

$$BIC = -2LL + Ln(N)K$$

where LL is the value of the log-likelihood function, K the number of parameters and N the sample size. This tests are calculated for models with different number of classes. The final number of classes selected is the one for which the value of the test is the smallest.

5 Dataset and variables

Our database consists of the ticket sales by the Royal Danish Theatre during the period 2010/'11 to 2012/'13. A total of 250170 bookings records are included in the dataset which involved 23 productions and 377 performances [4]. For each ticket reservation we have the following information that allow us to identify the choice done and customers' characteristics: name and address of the buyers, time and date of the purchase, price paid, price zone and price type.
The independent variables that enter in the model as choice's attributes are:

- *Price* (in DKK)
- *Seat category*: a dummy variable for each seat category, ranked from 1(the cheapest) to 5 (the most expensive).
- *Wkend*: it takes value one when the performance is either a weekend matinee or it is run on Friday/Saturday evening or in a public holiday day.
- *Wkday*: it takes value one when the performance is run during the weekdays.

Seat1 and *Wkday* are used as baselines in order to guarantee identification of the model. *Price* and *Seat category* variables aims to capture the tradeoff behaviour between cheap seats with low visibility and/or acoustics and more expensive high quality seats. As the number of seat categories has changed through the period under examination, for productions with more than five price zones, we have aggregated them into five seat categories. [5]

Table 2 reports an example on how the 8 seat price categories of the production "Tannhäuser" has been aggregated. The baseline is the production "Boris Godunov" The other two variables reflect the choice of the day of performance. As Corning and Levi (2002) has shown, these variables affect the performance-level demand. We have choosen only two variables

[4]For the complete list of production see the Appendix

[5]The rule of thumb followed is to consider as a baseline a production of the same genre in which the theatre was divided in 5 price zones: each new zone is associated with the baseline that has the smallest difference in price of a standard ticket. The price of the new seat categories are calculated as the average of the price of the original categories that has been aggregated to assemble the new categories

Seat category	**Price**	**Seat category**	**Price**	**New Seat category**[6]	**New price**
1	115	1	125	1 (1,2)	160
2	375	2	195	2 (3,4)	345
3	565	3	295	3 (5)	525
4	715	4	395	4 (6,7)	720
5	895	5	525	5 (8)	895
		6	645		
		7	795		
		8	895		

Table 2: Aggregation of seat categories

to characterize the day of the performance: we have excluded a dummy indicating whether the performance is the opening performance. The reason is that no price discrimination is applied for such kind of performancy. Moreover, the weekend variable include both the Friday/Saturday evening performance and the Sunday matinee. Indeed, from the data set we can observe that Sunday matinees constitute a small fraction of all the performances and they are not available for all the productions. Moreover, we note that basically, price of Sunday matinee and Friday/Saturday night are homogeneous across productions.
In addition, in our model we have also included choice invariant variables. These are related to customer's characteristics, that are inferable by the ticket type purchased, and to the characteristics of the production. Concerning the first set we have:

- *Young*: it takes value one when the customer is a student or a young person
- *Senior*: it takes value one when the customer is a senior citizen
- *Loyalty*:it takes value one when the customer has bought a loyalty card
- *Subscriber*: it takes value one when the customer is a subscriber
- *Foreign*: it takes value one when the customer does not live in Denmark
- *Period*: a dummy variable for each period before the performance in which the ticket has been sold

A note concerning the last variable: we have considered for each observation how many days before the performance the ticket has been sold. We have considered the distribution of these days among the observations and identified four quartiles: each quartile represent a period in the sale horizon, in particular: $1st$ period when the ticket is sold more than 232 days before the performance; $2nd$ period between 64 and 323 days; $3rd$ period between 19 and 64 days; $4th$ period until 19 days before the performance. These dummy variables are used in the MNL model, while in the LCM model a continuous variables denoting how many days before the performance the ticket has been sold is used.
Concerning the attributes of the production, these are taken from Bille *et al.* [2015] we use the following variables:

- *Opera*, *Ballet*, *Play*: dummy variables that capture the genre of the production and customer's taste

- *Newness*: for this attribute we have two dummy variables that measure the degree of newness/innovation in the performance.

- *New DKT*: it takes value one when the production is run for the first time at Royal Danish Theatre.

- *Review*: three dummy variable, respectively for a *Bad*, *Average* and *Good* newspaper reviews of the performance.

- *Audience evaluation*: three dummy variable, respectively for a *Bad*, *Average* and *Good* audience evaluation of the performance.

All these variables are included in the MNL model, while in the LCM we have included only the variables related to the genre of the production.
Some remarks about the production attributes variable:
In Bille [2015] data for the audiences evaluation of the productions have been collected every season. In every season a questionnaire was sent to the audiences at 5 operas, 5 plays and 5 ballets. For each production about 110 questionnaires were sent out, summing up to about 1650 questionnaires each season. During all the seasons the response rate has been around 52% (ranging from 49% to 60%). The quality of the performance was measured on a scale from 1-5 (where 1 is low quality and 5 high quality). Data for the professional reviewers evaluation of the productions have been collected every season as well. Similarly, reviews of the Royal Theatres productions in all the major Danish newspaper (9 newspapers) have been collected. Two independent researchers have been reading all the reviews and rated the quality of the productions based on the reviewers opinion. In this way the quality has been indexed on a scale 1-5, and the two researchers has in the case of inconsistent evaluations agreed on the final index on the evaluation scale 1-5.
Based on these measures, we have identified three categories for both audiences' evaluation and review variables: bad, average and good.
The degree of newness in the productions has been assessed by an expert in theatre science. A Mozart opera can be very traditional performed or it can be performed in a very traditional way. Likewise, a brand new production can be very traditional or it can be experimental and groundbreaking. This variable takes to levels: traditional or innovative.
Table 3 sumarizes the variables used in our models.

As already said, the combination of seating area and day of performance define the customer's choice set. One of the main difficulty in the model set up is the identification of the choice set of each booking. Indeed, the seat categories available for an individual depends on the choices made by individuals who have already bought a ticket. Since no performance are totally sold out, we do not have information on whether, at some stage

Level	Variable	Description	Type
Alternatives	*Price*	Price in DKK	Continuous
	Seat	Seat category (5 level)	Dummy
	Wkend	Friday/Saturday evening, Sunday mattinee	Dummy
	Wkday	Weekdays	Dummy
Customer	*Young*	Under 25 years /Student	Dummy
	Senior	Retirees	Dummy
	Subscribers	Subscribers	Dummy
	Loyalty	Customers with a loyalty card	Dummy
	Foreign	Equal 1 if customer does not live in Denmark	Dummy
	Period	4 Periods of purchasing (only MNL)	Dummy
	Days	no. of days before the performance the ticket has been sold (only LCM)	Continuous
Production	*Genre*	Opera, Ballet and Play	Dummy
	Newness	Degree of newness/innovation, 2 levels (only MNL)	Dummy
	New DKT	First time in Denmark (only MNL)	Dummy
	Review	Newspaper review, 3 level (only MNL)	Dummy
	Evaluation	Audience evaluation, 3 level (only MNL)	Dummy

Table 3: Variables used in MNL and LC models

of the sale period, a single region of the theatre is sold out or, on the contrary, tickets for that zone are available. However, we can notice that, in general, tickets for all the seat categories are sold until the last few days before the performance starts. Hence we assume that for each individual the choice set includes all the seat categories. This assumption seems realistic as the theatre management has confirmed how, in most cases, there are available seats for all the price zones just before the beginning of the performance. The only exceptions regards the *Senior* category, for which in some cases, for a specific choice by the theatre management, not all the price zones are available. Clearly, In estimating the model we take into account the situations in which this category has a reduced choice set.

The identification of the choice set along the day of performance is easier: for each production we consider the last Friday/Saturday evening and weekday performance. Assuming this is the chronological order, all the bookings made after the last ticket sold of the last Friday/Saturday evening performance will have a reduced choice set as it will not include the weekday performance.

Table 4 illustrates how the choice set generation process works for the production "Così fan tutte". In the context of this example, all bookings made after (a) face 5 alternatives instead of 10 (assuming that all the price zones of the theatre are available)

Date and time of performance	Dummy variable = 1	Date last ticket sold
11-10-2011 19:30	$Wkday$	-
14-10-2011 19:30	$Wkend$t	-
16-10-2011 15:00	$Wkend$	-
25-10-2011 19:30	$Wkday$	-
27-10-2011 19:30	$Wkday$	-
30-10-2011 15:00	$Wkend$	-
02-11-2011 19:30	$Wkday$	-
06-11-2011 15:00	$Wkend$	
10-11-2011 19:30	$Wkday$	-
19-11-2011 19:30	$Wkend$	17-11-2011 10:38 (a)
21-11-2011 19:30	$Wkday$	-

Table 4: Choice set generation process

6 Model estimation results

6.1 Multinomial logit model

The MNL model is estimated with Biogeme [Bierlaire, 2003][7] and their results are shown in Table 5. The multinomial logit model is linear in the parameters specification, including the characteristics of the alternatives and their interactions terms in order to accomodate taste variations due to customers' and performances characteristics. Models with different interactions terms are estimated and compared by using the non-nested hypothesis test developed by Horowitz (1982).

Table 5 displays the significant coefficients [8] of the MNL specification that has shown a better fitting model. The variable $Play$, $Seat1$, $Period1$, $Wkday$, $Review\ bad$ and $Evaluation\ bad$ are used as base variables to allow for identification of the model. In the final specification we allow the $Price$ sensitivity to takes different value according to the production characteristics and the period in which customer buys the ticket; whereas the marginal utility of the $Seat$ and $Wkend$ interacts with the $Foreign$ and the different customers' categories.

The $Price$ coefficient is negative as expected. However, the heterogenetiy of the price sensibility for the theatrical experience is revealed through the coefficients of the interaction terms. In particolar, the interaction with the period of purchasing reveals this pattern: the price coefficient increases as we consider bookings made long before the day of the performance, reaching a positive value in the first period of the time horizon (in the first period a coefficient of -0.00203+0.00216 = 0.00013). For this portion of consumers, the theatrical experience is configured as a Veblen good. Typically, the earlier ticket buyers are subscribers [Drake, 2008; Tereyagoglu *et al.*, 2012] who, as empirical evidence has shown, are less responsive to ticket price changes [Felton, 1994]. This is quite logic as

[7] Biogeme is a free software specifically designed for discrete choice models. It can be downloaded from http://biogeme.epfl.ch/home.html)

[8] All variables are significant except the interaction terms between *price* and *ballet* and between $Wkday$ and *loyalty*

	Coefficient	*t-stat*
Price	**-0.00203**	-17.07
Price-Period1	0.00216	38.90
Price-Period2	0.00139	36.37
Price-Period3	0.000360	10.22
Price-Aud. Evaluation average	-0.000142^{**}	-1.93
Price-Aud. Evaluation good	0.000858	16.81
Price-New DKT	0.000918	21.64
Price-Newness1	-0.00106	-16.96
Price-Newness2	-0.00128	-21.70
Price-Opera	-0.000574	-14.39
Price-Review average	0.000377	8.85
Price-Review good	0.000517	9.64
Seat 2	**0.648**	36.90
Seat 2 - Foreign	0.0913^{*}	2.26
Seat 2 - Loyalty	0.530	2.98
Seat 2 - Senior	0.543	3.67
Seat 2 - Subscriber	0.898	26.92
Seat 2 - Young	-0.222	-9.33
Seat 3	**1.35**	53.13
Seat 3 - Foreign	-0.0782^{*}	-2.04
Seat 3 - Loyalty	0.306^{**}	1.80
Seat 3 - Senior	1.84	14.16
Seat 3 - Subscriber	1.03	31.38
Seat 3 - Young	-0.622	-24.94
Seat 4	**1.80**	52.78
Seat 4 - Foreign	0.151	4.17
Seat 4 - Loyalty	0.534	3.27
Seat 4 - Senior	1.52	11.66
Seat 4 - Subscriber	1.28	38.12
Seat 4 - Young	-1.29	-46.38
Seat 5	**1.94**	43.94
Seat 5 - Foreign	0.454	12.71
Seat 5 - Loyalty	0.448	2.74
Seat 5 - Senior	1.49	11.36
Seat 5 - Subscriber	1.40	39.08
Seat 5 - Young	-1.48	-46.38
Wkend	**0.214**	36.74
Wkend - Foreign	0.357	19.41
Wkend - Senior	-0.751	-30.91
Wkend - Subscriber	-0.192	-21.14
Wkend - Young	-0.143	-11.55
No. of observations		250170
ρ^2		0.083
Adjusted ρ^2		0.083
Null log-likelihood		- 573738.544
Final log-likelihood		-526059.818

$^{**}p = .10$ $^{*}p = .05$

For all the others variables $p = .001$

Table 5: Estimation of multinomial logit model

the committment of attending a performance so long time in advance denotes a strong willingness for that theatrical experience. As Drake *et al.* [2008] claims, there is a direct relation between the demand rate and the inventory level: the seats that are already sold at a given price are more valuable than the ones that remain, as typically the latter are further away from the stage. Also within the same seat tiers there are seats that guarantee a better viewing of the performance[9]. Moreover, as Corning and Levy [2002] notice, single ticket purchasers have a higher opportunity cost of time compared to subscribers, so they prefer to preserve themselves for "flop": this can be done buying the ticket in a later stage, after a period in which crucial information for the purchasing decision are acquired. Figure 2 depicts the total sale of subscribtion and standard tickets in relation to the time before the performance. We consider as the beginning of the time horizon 62 weeks before the show. For subscribers, the sale patterns reaches different peaks until around 30 weeks before the performance, and then monotonically decrease. In contrast, for standard ticket buyers, the pattern is monotonically increasing and reaches a pick one week before the performance.

Figure 3 shows the cumulative distribution over time of the sales of each seat category,

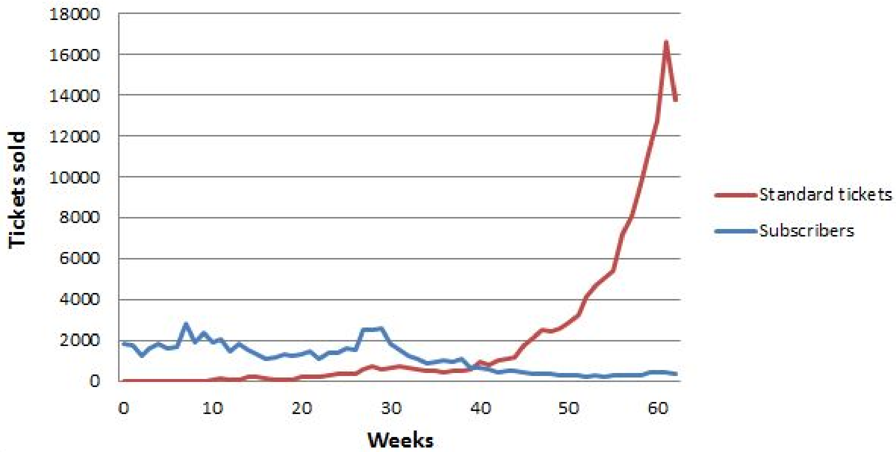

Figure 2: Total sales of subscription and standard tickets over time

considering the 60 weeks before the date of the performance. It is evident how the most valuable seats are sold in the beginning of the sale period, while, as we approach to the date of the performance, there is an increase in lower quality seats sales. This pattern has been empirically demonstrated by Tereyagoglu *et al.* [2012]. According to Figure 3, when we consider the total sales of the fifth seat category, 50% of them are already sold around 16 weeks before the performance; 12 weeks for the fourth category; 8 weeks for the third category; 6 weeks for the second category and only 4 weeks for the cheapest seat category. Concerning the interactions with the production characteristic, the price coefficient for *opera* is slightly smaller compared to the *play* genre, while the interaction

[9] An exception occured when the customer intentionally delays the ticket purchase when it is expected that the theatre uses a discount policy for tickets sold very close to the performance

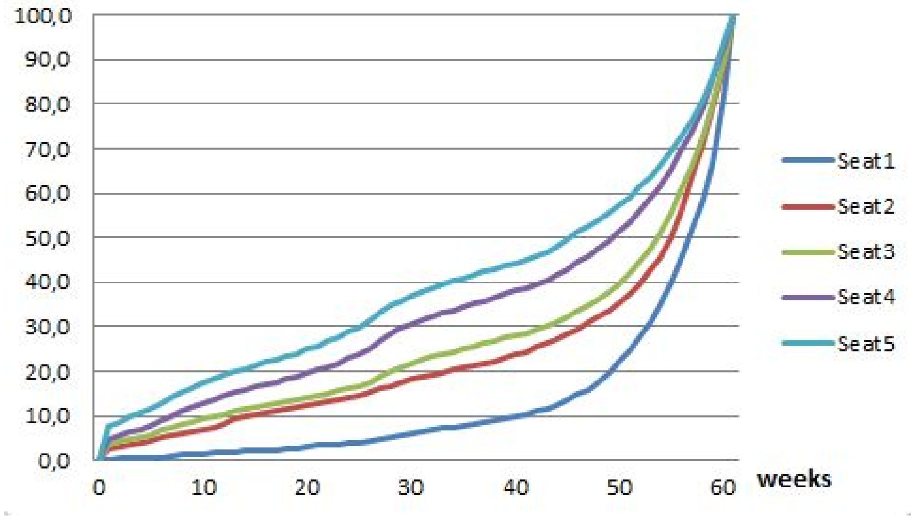

Figure 3: Cumulative distribution over time of each seat category

with *ballet* is not significant. Moreover, the price coefficient decreases as the degree of newness/innovation increases, showing that the audience prefer traditional and less risky productions compared to those more experimental. The quality of the production as reported by *reviews* has a positive impact on the customer's utility as well as, to a greater extent, those productions that are performed for the first time at the Royal Theatre. Surprisingly, the effect of audience evaluation is not monotonically increasing in size: the *average evaluation* coefficient compared is negative where the *bad evaluation* is the baseline, although in terms of significance, the interaction with *average evaluation* account for the lowest absolute value of the $t-test$ (-1.93)

With regard to the seat quality, the coefficients reflect an expected pattern for the standard ticket buyers (which coefficient is the one without interaction terms), senior, subscribers and customers affiliated with a loyalty program: an increase of the quality of the seat leads to a greater utility. In particular, among these categories, for *Senior* and *Subscribers* this pattern is more evident, followed by *Loyalty* and *Standard*. Also the foreigner customers (87% of which are standard ticket buyers), show a similar tendency with a larger coefficient compared to Danish standard ticket buyers.

The highest marginal utility for the *Senior* and *Subscribers* category can found an explanation in the well known theory of rational addiction developed by Stigler and Becker [1997]: the consumption of cultural goods (a theatre production in our case) increase the consumers future capacity to appreciate it, through the "learning by doing" process. Hence, previous exposition to the cultural goods to leads to a growth in consumption and therefore to an increasing willingness to pay. In this sense subscribers and senior are type of customers who have accumulated consumption capital through their past consumption: the former because a subscription implies high frequency of the theatre, the latter because of the age component. These customers, more than others, pay attention to seats who provide a better quality of the theatrical experience from both the acoustic and visual

perspective.
The $Young$ category has the lowest value of the marginal utility and it is not monotonically increasing with respect to seat quality, with the largest value in correspondence with the third seat category. Therefore, it seems that this category would not consider the possibility to buy expensive seats and pay little attention to the seat quality
Figure 4 shows more graphically for each category the relation between the utility function to the level of the seat attribute. As the figure seems to suggest, except for young

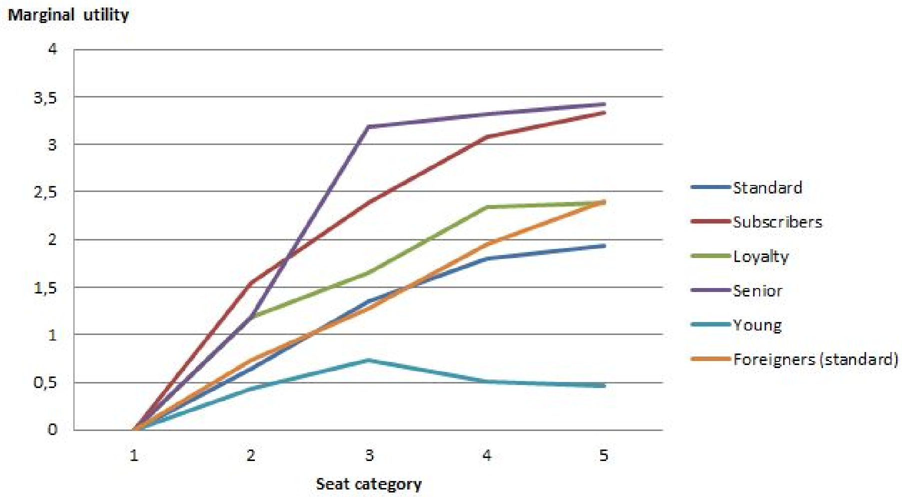

Figure 4: Quality of seat in relation to the utility function

customers, the relation between quality of seat and customers' utility is approximately increasing and concave, meaning that as we increase the level of seat quality, the difference in utility gets smaler and smaller.
Finally, we notice that, with the exception of $Senior$, weekend performance are preferred over the weekday performance, in particular by the foreigners standard ticket buyers, followed by Danish standard ticket buyers, $Young$ and $subscribers$. This result is probably due to to a greater flow of tourists in the city of Copenhagen during the weekend. The negative value for $Senior$ (0.213-0.510 = 0.297) can be explained considering that this category is rich in time and therefore prefer the weekday alternatives which is cheaper. However, compared to the seat attributes, the day of the performance has a lower impact on explaining the choice of ticket.

6.2 Latent class estimation

In the Latent class model we aim to identify distinct group of theatregoers' according to their behaviour with respect to the type of ticket to purchased. We initially assess the number of classes in the LC model by BIC and AIC. These statistics indicate whether the complexity of the model, i.e the number of parameters to be estimated, can be compensated by an improvement in the value of the log-likelihood. Table 6 summarizes the statistics for models with 1,2,3 and 4 classes. The results show that as the number of

No. of classes	Log-likelihood value	AIC	BIC
1	-540535,3380	1081082,6759	1081145,2553
2	-530590,2024	1061224,4048	1061453,8625
3	-524502,4273	1049080,8545	1049477,1906
4	-521576,2680	1043260,5359	1043823,7503

Table 6: Criteria for determining the optimal number of classes

classes increases, the model fits the data better. Increasing further the number of classes, we obtain the optimal model with 7 classes. However, as the number of segments increases to more than 4 classes, we obtain some small segments sizes that make the parameter estimated unstable. For this reason, and also for an easier interpretation of the model, we adopt the 4 class solution.

The explanatory variables of the choice model are: $Price$, $Seat$ and $Wkend$, with $Seat1$ and $Wkday$ set to 0 as base variables. We include the membership function, in order to assign individuals to classes according to their characteristics and the choice situation. The variables employed for the membership function include the dummy variables related to: the customer ticket's category and genre of the production. Moreover, we include a variable indicating how many days before the performance the ticket has been bought: compared to the MNL model, where this variable is used as a categorical variable in 4 levels to be interacted with price, we use $days$ as a continuos variable in the membership function that contribute to the class assignment of individuals

Table 7 reports the results derived from the Latent Class model, which is estimated using the software Latent Gold Choice [Vermunt and Magidson, 2005]. Given that the magnitude of the coefficients of the choice model can not be compared between different classes due to scale parameter [Carrier, 2008; Hetrakul and Cirillo, 2013], the different behaviour of the classes are compared by their willingness to pay for the choice attribute. As regards the membership function, the coefficients indicate how much the variables accounts for the belonging to that particular class: the variables are interpretated in relation to the Class 4, normalized to zero for identification of the model

In Table 7 we report for each parameter the result of the Wald test. The Wald test, which is largely employed in latent class model, is a test for the equality of effects between classes, indicating whether a variable is equal across classes and so, is class independent. In our model the null hypothesis is rejected for all the predictors and covariates, indicating that all the variables choosen are useful in discriminating individuals in classes.

Classes are numbered in order of size.

Class 1 accounts for 48.4 % of the market and exhibit an expected pattern: price coefficient is negative and individuals in this class increase their utility along with the increase of the quality of seat. Moreover, this class prefer weekend performance than weekday ones. This class shows a high willingness to pay for a theatre ticket, but not the highest among classes.

Parameter	**Class1**	**Class2**	**Class3**	**Class4**	Wald test	p-value
Price	-0.0039	-0.0001	-0.0003	-0.1091	1224.54	0.00
	(-30.32)	*(-0.29)*	*(-2.13)*	*(-11.45)*		
Seat2	10.7610	0.0614	0.1507	7.4508	55.6901	0.00
	(1.38)	*(0.69)*	*(7.01)*	*(1.18)*		
Seat3	11.8896	1.8220	0.1364	28.2045	522.1306	0.00
	(1.52)	*(18.84)*	*(4.28)*	*(11.74)*		
Seat4	12.8816	2.8707	-0.1115	27.6766	1055.6425	0.00
	(1.65)	*(29.70)*	*(-2.36)*	*(10.72)*		
Seat5	14.0908	2.2991	-2.5306	34.1273	478.3154	0.00
	(1.82)	*(18.25)*	*(-4.43)*	*(10.42)*		
Wkend	0.3495	-0.0941	0.1055	-0.4873	1691.2595	0.00
	(.30.32)	*(-0.29)*	*(-2.13)*	*(-11.45)*		
Membership function						
Standard	3.5465	10.2095	2.6567		97.5406	0.00
	(6.75)	*(1.98)*	*(4.83)*			
Subscribers	2.0865	9.6714	0.7470		154.7725	0.00
	(3.99)	*(1.88)*	*(1.37)*			
Young	0,4906	-0.4604	1.0377		36.1000	0.00
	(0.94)	*(-0.85)*	*(1.91)*			
Senior	-20.0132	-1.2175	-18.6624		18.4787	0.00
	(-3.31)	*(-18.66)*	*(-3.12)*			
Loyalty	-3.4969	4.1490	-4.7088		32.0894	0.00
	(-0.39)	*(0.41)*	*(-0.53)*			
Opera	1.7714	5.0029	2.8948		503.5944	0.00
	(6.75)	*(1.98)*	*(4.83)*			
Ballet	5.4112	7.0468	6.3155		326-7014	0.00
	(1.08)	*(1.41)*	*(1.26)*			
Play	-9.7429	-4.8584	-8.3682		523.7187	0.00
	(-1.76)	*(-0.88)*	*(-1.51)*			
Days	0.0059	0.0025	-0.0042		977.2111	0.00
	(11.12)	*(4.82)*	*(-7.77)*			
No. of observations	250170					
Adjusted ρ^2		0.091				

Table 7: Estimation of Latent class model

Instead, Class 2 is characterized by the largest willingness to pay, as the price coefficient is negative but very close to zero. This class prefers weekday performances and the most expensive seats; however it exhibits the greatest marginal utility for the fourth seat category. This class contributes 24.4 % of the market.

Classes 3 and 4 have as a common characteristic that both exhibit low willingness to pay compared to Classes 1 and 2. However, they differ from each other significantly in some aspects: Class 3 is slightly smaller than Class 2, accounting for 24.1 % of the market. The individuals of this class prefer weekend performance and the cheapest seats: the coefficient for the fourt and fifth seat categories is even negative, as if cusomers of this class would not consider the possibility to buy expensive seats.

Class 4 is clearly the smallest one, accounting for only 3.1 % of the total market. As for the Class 2, individual of Class 4 prefer weekday performance and exhibit a a stronger preference for the most expensive seats, even if the willingness to pay for seat tiers is the lowest among all the classes.

In terms of customers' characteristics, we can notice from the coefficient of the mermership function, how Class 3 and 4 are strongly characterized by the age component: Class 3 can be considered representative of *young* customers as, in opposed to other categories, *young* has it largest coefficient in this class. This results confirm what we obtained with the MNL model regarding a low willingness to pay by young customers. Class 4 is composed mainly by *senior* customers: this is evident observing how its coefficient is negative for all the other classes. However, considering that Class 4 is very small, we can deduce that a significant share of *senior* are included in Class 2, given that in the first and third class its coefficient are decisively negative.

Standard and *Subscribers* have always a positive coefficient, suggesting that these categories are distributed across the first three classes; while the coefficient for the customers engaged in a *loyalty* program has a $z - value$ close to zero in all three classes that prevent us from making considerations.

The assignment of individuals to classes, based on the maximum posterior probability, can helps us in understanding the class composition. In fact, once the parameters of the model are estimated, they can be used to calculate the conditional individuals' probability of membership in each class by means of Bayes's theorem:

$$P(s \mid j, \hat{\eta}) = \frac{\hat{P}(j \mid s, \hat{\eta}) \cdot \hat{P}(s \mid \hat{\eta})}{\sum_{s=1}^{S} \hat{P}(j \mid s) \cdot M_{is}} \tag{12}$$

Equation (12) give us the probability that the individual belongs to class s conditional on the choice made and his/her characteristics (which parameters are estimated). On the numerator we have the estimated choice probability for the choice made, given the class s, multiplied by the prior estimated class probability. On the denominator we find the probability to choose the alternative j expressed, in the spirit of latent class, as a sum of MNL moderated by the size of each class. Indeed, the denominator is equal to expression (8) and (10).

Each individuals are assigned to the latent class s that provide the maximum value of (12). Based on this procedure, we can see how the categories are distributed across classes, as Figure 5 shows. While in the MNL model the customers' behaviour is distinguished according to their price category, in the LCM we can notice some forms of heterogeneity also within category, even if some patterns resulting from MNL are supported. The fact that almost all *young* customers (62.3 %) are classified in the third class confirms their low willingness to pay, the low utility gained by high quality seats and a preference for the weekend performances. However, a non-negligible share of *young* customers (28.7 %) are found in the first class. Probably, given the high value of willingness to pay for Class 1, such customers are young subscribers. We should also consider the fact that in some cases the youth subscription make it feasible for families to subscribe and include their children. In this case, the choice of these *young* customers depends on the one made by the family components that are subscribers.

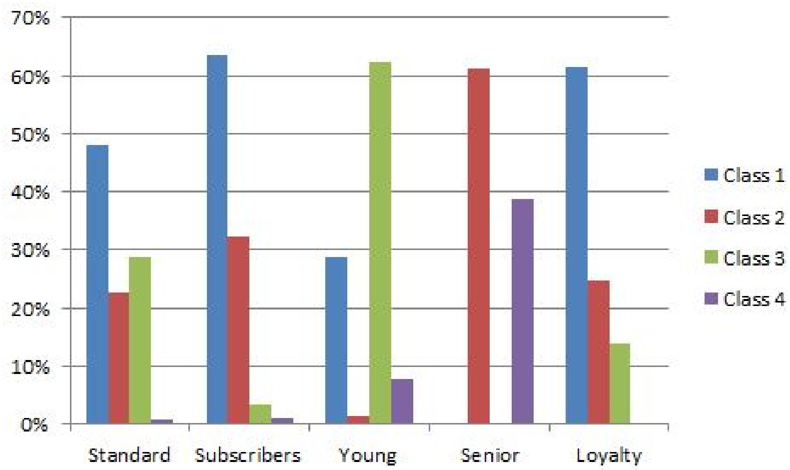

Figure 5: Distribution of customers across classes

Subscribers and *loyalty*, representative of customers who frequently attend the theatre, are mainly concentrated in the first two classes (in particular the first one), confirming that these categories are characterized by high willingness to pay and a preference for the most expensive seats.
Almost half (47.9 %) of *standard* tickets buyers, representative of infrequent theatre attendance, are classified in the first class; but a significant share are found also in Class 2 (22.6 %) and Class 3 (28.7 %). Hence, there is a sort of heterogenetiy within this category, even if the majority of them are included in the two classes with the highest willingness to pay.
Senior customers are clearly split into the second and fourth classes which are antithetical each other from the willingness to pay perspective, but similar in their preference for weekday performances - the latter aspect confirms the results of the MNL model. The majority (61.2 %) of *senior* customers are classificated in the second class, confirming that this category has the greatest willingness to pay. However, 38.7 % of senior customers are found in the fourth class, which is the one with lowest willingness to pay. Both classes exhibit a preference for seats with high quality, but while in the second class we find that the 4th seat category has the highest coefficient, in Class 4 both the 3th and the 5th seat category are preferred to the 4th: this different pattern can explain the MNL result in which, for this category, the marginal utility of the seat attribute is not monotically increasing with respect to its quality.

Concerning the genre, we notice a positive value of the coefficient for *opera* and *ballet* and a negative value of the coefficient of *play*, which suggest us, by implication, that individuals of Class 4 are *play* attendants.
In Figure 6, the classification procedure is made on the basis of the genre of productions. In this way, we can verify whether customers' behaviour is homogeneous or not across different types of theatrical productions. From Figure 6, we can notice that people who

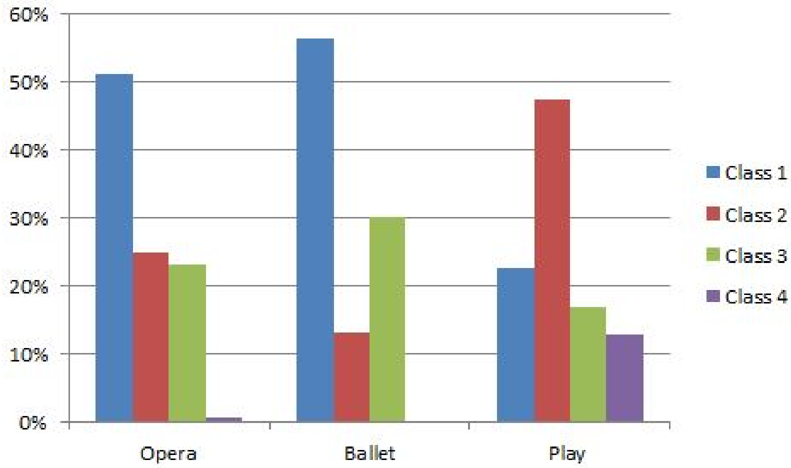

Figure 6: Distribution of latent classes across type of production

attend *opera* performances can be clustered in the four latent classes with about the same proportion resulting from the LC model. Hence, about half (51.2 %) of the opera's customers belong to the first class and the other half are more or less equally shared by the second and the third class (respectively 24.8 % and 23.2 %). A high amount of *ballet*'s customers belong to the first class (56.4 %), but the remarkable aspect is that Class 3 individuals are more than twice as big as Class 2 (respectively 30.2% and 13.2%). *Plays* present a particular pattern: indeed, almost all individuals of Class 4 attend plays, that accounts for 13% of the total attendance of this production genre. However, their presence is counterbalanced by a large presence (47.3 %) of the class with the highest willingness to pay.
This framework suggest it is better to schedule plays on weekday. Moreover, in plays we find, compared to the other genres, a higher heterogeneity in terms of willingness to pay, given the significant presence of individuals of Class 2 and 4. From this point of view, ballet seems to be the most homogeneous genre as the share of Class 2 is low while the presence of individuals of Class 3 is substantial.

Finally, looking at the coefficients of the variable *day*, the negative coefficient in Class 3 suggests that the members of this Class prefer to buy theatre tickets in a period close to the date of the performance: the opposite holds for Class 1 and 2, which coefficients are positive. In Figure 7 we classify individuals by the purchase period measured as days before the performance. What appears evident from Figure 7, is the opposite trend by Classes with different willingness to pay. At the beginning of the sale period, a big share of tickets (97.8 %) are sold to customers of Class 1 and 2, confirming the positive relationship between willingness to pay and early purchase of tickets. As we approach to the day of the performance, the share of these two Classes (in particular Class 1 as suggested by the magnitude of the *days* coefficient) decrease: in the period until 14 days before the performance, 32.7 % and 22% of the tickets sold are bought by customers that are classified

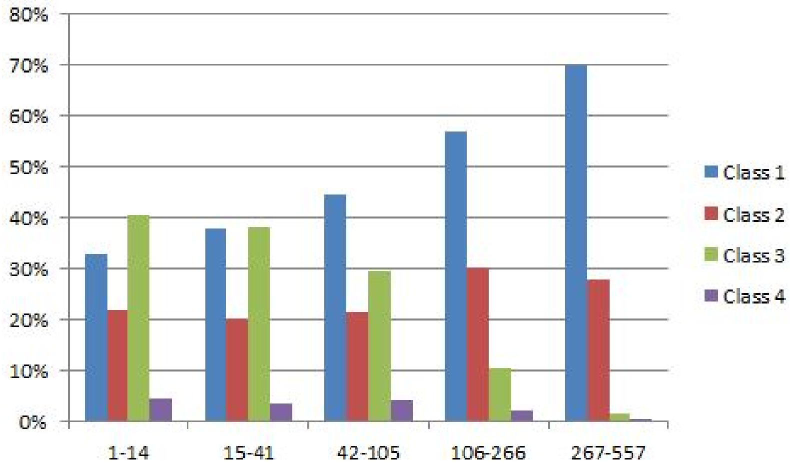

Figure 7: Distribution of latent class by purchase period

respectively in Class 1 and 2. Conversely, Classes characterized by low willingness to pay tend to purchase theatre tickets in the latest stage of the sale period. This finding is more evident for Class 3. Indeed, the trend of Class 4 is quite stable from the middle of the sale period to the last days before the performance. Instead the rate of individuals of Class 3 who buy a ticket increases as we approach to the day of performance: in the last 14 days, the relative majority (40.6 %) of customers who buy a ticket belong to this Class.

In summary, the analysis suggests four typology of classes:
Class 1 accounts for 48.4 % of the market. This segment embrace theatregoers who has a high willingness to pay for a theatre ticket and gain a greater utility as the quality of the seat increases. They are early-buyers and prefer weekend performances. This segment represents the majority regarding opera and ballet productions, but not with regard the plays. Individuals of this Class are composed mainly of standard ticket buyers, subscribers and customers enrolled in a loyalty program.
Class 2 has a size of 24.4 % and represents customers with the highest willingness to pay. Similar to Class 1, this segment prefer the most expensive seats and tend to buy tickets in the early stage of the sale period. However, they prefer weekday performance and represent the prevailing Class in plays. A big share of senior customers belong to this Class which includes also standard ticket buyers, subscribers and customers enrolled in a loyalty program.
Class 3 account for 24.1 % of the market. It represents mainly young customers and standard ticket buyers with low willingness to pay. Members of this segment prefer cheapest seats not considering the possibility to buy expensive seats. They prefer weekend performances and tend to buy the ticket in the latest stages of the sale period. This class is presented in all the genre of performances but particularly in ballet productions.
Class 4 is very small with a size of 3.1 %. This is the Class with the lowest willingness to pay, and can be found mainly in plays. As Class 2, this Class prefer the most expensive

seats and weekday performances. Members of this Class are used to buy tickets starting from the middle of the sale period. This class is almost entirely composed of senior customers.

Table 8 summarizes the main characteristics of the four classes identifed by the Latent Class Model. It is interesting to compare the Classes obtained in this model with the

	1	**2**	**3**	**4**
Share	48.4 %	24.4 %	24.1 %	3.1 %
WTP	High	Highest	Low	Lowest
Seat	Expensive	Expensive	Cheap	Expensive
Day	Weekend	Weekday	Weekend	Weekday
Genre	Opera and Ballet	Play	Opera, Ballet and Play	Play
Purchase period	Early buyer	Early buyer	Late buyer	Mid-late buyer
Composition	Standard,Subscribers,Loyalty	Senior and Subscribers	Young, Standard	Senior

Table 8: Summary of latent classes

one resulting from Grisolia and Willis's [2012] model. Even if the two authors consider a different set of choice's attributes related to a theatre production (price, review, word of mouth, repertory classification, author, review), we can find, by the membership function, some similarities. Grisolia and Willis [2012] identify three classes of theatregoers: their third Class denoted as the intellectual class, which is composed by mature people and high frequent attendees and exhibit the largest willingness to pay, seems to confirm the characteristics of our Class 2. Indeed, also in our cases senior (mature people) and subscribers (high frequent attendees) are characterized by the highest willingness to pay. The second Class in Grisolia and Willis's [2012] can be associated with our Class 3: both Classes are composed of young people, occasionaly attendees [10] and exhibit a low willingness to pay. A different discourse can be made for Grisolia and Willis's first case which, in their model, is composed of affluent people who attend theatre occasionaly. In this case, we don't find a correspondence with our Class 1 because we do not have information about customers' income and, moreover, our first Class is composed by both subscribers and standard ticket buyers.

6.3 Statistical test to compare models

We can compare our models in terms of goodness of fit. In general terms, for both models the likelihood ratio test [11] indicate that these models are better than the null model, in which all parameters are set to zero. LCM performs better than MNL, as can be seen from their log-likelihood values and ρ squared. As these two models are non-nested, we use the Horowitz test two compare model fits of MNL and LCM. The null hypothesis of the test is that the model with the lower adjusted rho-squared is preferred. The decision

[10] From Figure 5 we can see that a significant share of standard ticket buyers are included in the third class, while it is not the same for subscribers and loyalty.

[11] This test is given by: $LR = -2 * (LL(\hat{\beta}) - LL(0))$ where $LL(\hat{\beta}))$ is the log-likelihood at the estimated parameters while $LL(0)$ is the log likelihood for the null model. LR is always positive, and distributed chi-squared with degrees of freedom equal to the number of parameters

rule for which the null hypothesis is rejected is given by:

$$\phi[-(-2(\rho_H^2 - \rho_L^2) \cdot LL(0) + (K_H - K_L))^{1/2}] < \alpha$$

where ϕ is the standard normal cumulative distribution function, ρ_H^2 and ρ_L^2 are respectively the larger and the smaller value of adjusted rho-squared; K_H and K_L are the number of the parameters in the model with the larger and smaller value of rho-squared; and α is the significance level.

The null hypothesis is rejected, supporting the argument for which the LCM model fits the data better.

6.4 Willingness to pay measures

Measuring the willingness to pay (WTP) for the change in the level of attributes is very important in order to adopt an appropriate pricing strategy. In the MNL framework, the WTP of an attribute k is given by the ratio of the coefficient of the attribute (β_k) and the price coefficient β_p:

$$WTP_k = \frac{\beta_k}{\beta_p} \tag{13}$$

However, (13) provides a point estimate, while it is known that the parameters in (13) have a confidence interval and that they distribute asymptotically normal. A solution proposed in the literature is to calculate the confidence interval of the ratio using the Delta method, which allows to determine accurately the standard error of the ratio of two estimators [Daly *at al.*, 2012].

In particular, the standard error of the ratio between two parameters estimated can be measured by the following [Bliemer and Rose, 2013]:

$$SE(\beta_k/\beta_p) = \sqrt{\frac{1}{\beta_p^2} \cdot \left[SE(\beta_k)^2 - \frac{2\beta_k}{\beta_p} \cdot COV(\beta_k, \beta_p) + \left(\frac{\beta_k}{\beta_p}\right)^2 \cdot SE(\beta_p)^2\right]} \tag{14}$$

Table 9 reports for each customers' category the WTP (in Danish crowns) and its confidence interval obtained with MNL model, for switch from the first seat category to a higher quality seat and for switch from a weekday to a weekend performance. Apart from the standard ticket buyers, for the other customer's category it is taken into account that the coefficient attribute is obtained as the sum of the seat category coefficient and the coefficient of the interaction term. Hence, in calculating (13), the standard error of the sum of the two parameters estimated is considered. Given that price coefficients varies according to production's characteristics, for semplicity it is assumed a ballet performance with has bad review and evaluation; and that the customers buys the ticket in the last booking period. Clearly we don't report those attributes for which the WTP is either negative - as in the case of weekend performances for seniors, or the attribute coefficient is not significant, e.g weekend performances for loyalty customers.

Regarding the LC model, the WTP is obtained in a similar manner to MNL given that

Category	**Attribute**	**WTP**	**Standard error**	***t*-ratio**	**95% Confidence interval**	
Standard	Seat 2	319	15.22	20.96	289.17	348.83
	Seat 3	665	30.40	21.87	605.42	724.58
	Seat 4	887	39.33	22.55	809.91	964.09
	Seat 5	956	39.44	24.24	878.70	1033.30
	Wkend	105	6.53	16.08	92.20	117.80
Subscribers	Seat 2	762	42.82	17.79	678.07	845.93
	Seat 3	1172	62.26	18.82	1049.97	1294.03
	Seat 4	1517	78.81	19.25	1362.53	1671.47
	Seat 5	1645	82.65	19.90	1483.01	1806.99
	Wkend	11	3.55	3.10	4.04	17.96
Senior	Seat 2	587	78.87	7.44	432.41	741.58
	Seat 3	1571	108.41	14.49	1358.52	1783.48
	Seat 4	1635	108.22	15.11	1422.88	1847.11
	Seat 5	1690	108.72	15.54	1476.91	1903.09
	Wkend	-	-	-	-	
Loyalty	Seat 2	580	92.46	6.27	398.78	761.22
	Seat 3	816	92.63	8.81	634.45	997.55
	Seat 4	1150	97.74	11.76	958.43	1341.57
	Seat 5	1176	96.53	12.18	986.80	1365.20
	Wkend	-	-	-	-	
Young	Seat 2	210	13.88	15.13	182.80	237.20
	Seat 3	359	19.22	18.68	321.33	396.67
	Seat 4	251	13.17	19.06	225.19	276.81
	Seat 5	227	11.94	19.01	203.60	250.40
	Wkend	35	5.88	5.95	23.48	46.52
Foreigner (standard ticket)	Seat 2	364	25.36	14.35	314.29	413.71
	Seat 3	626	33.33	18.78	560.67	691.33
	Seat 4	961	48.13	19.97	866.67	1055.33
	Seat 5	1179	55.11	21.39	1070.98	1287.02
	Wkend	281	18.19	15.45	245.35	316.65

Table 9: WTP based on MNL for switching from Seat1 category and weekday performance

within each class the parameters are logit.

Table 10 shows the WTP for each latent class. We don't report the WTP for attributes that has a negative coefficient. From the LCM model it results that WTP in Class 1 and Class 2 are not statistically significant (with the exception of weekend performances for Class 1). For these attributes, we report the point estimate and not the confidence interval

In general, the WTP values seem large. There can be various reason for this: firstly, it might be that the customer play little attention to price when they select the ticket as the result of high inelasticity of the demand for theatre [Zieba, 2009; Grisolia and Willis, 2015].

Second, the models are based on a Revealed Preference dataset; hence we deal with individuals who have already decided to buy a theatre ticket. The purchase in itself implies that the WTP is higher than the ticket price (otherwise the individual would not buy the

Category	Attribute	WTP	Standard error	t-ratio	95% Confidence interval	
Class 1	Seat 2	2759	1993.337	1.38	-	
	Seat 3	3049	1993.316	1.52	-	
	Seat 4	3303	1993.374	1.66	-	
	Seat 5	3613	1993.37	1.81	-	
	Wkend	89	2.7492	32.37	83.61	94.39
Class 2	Seat 2	614	1746.646	0.35	-	
	Seat 3	18220	54062.16	0.34	-	
	Seat 4	28707	85418.41	0.34	-	
	Seat 5	22991	67957.04	0.34	-	
	Wkend	-	-	-	-	
Class 3	Seat2	502	115.4725	4.35	275.67	728.32
	Seat 3	454	67.1648	6.76	322.36	585.64
	Seat 4	-	-	-	-	
	Seat 5	-	-	-	-	
	Wkend	351	124.0801	2.82	107.80	594.19
Class 4	Seat2	68	56.87	1.19	-	
	Seat 3	258	6.7481	38.23	244.77	271.22
	Seat 4	253	6.6976	37.77	239.87	266.13
	Seat 5	312	6.9706	44.76	224.27	399.73
	Wkend	-	-	-	-	

Table 10: WTP based on LCM for switching from Seat1 category and weekday performance

ticket). Conversely, a Stated Preference experiment include the no-purchase option. In any case, it should be pointed out that the choice of which seat category to buy depends on the difference between WTP and the ticket price: for example, looking at the standard ticket buyers in Table 9, the difference between WTP for the fifth and fourth seat category is 70DKK. This implies that whether the difference in the ticket price between these two seat category is greater then 70 DKK, the customer will prefer to buy a fourth seat category ticket than the fifth seat category ticket.

7 Conclusions

In a period in which the public funds addressed to cultural organizations are decreasing and the performing arts organizations are struggling to attract a broader audience and to achieve a balance between revenue and losses; price discrimination strategy is emerging as a tool to achieve the organization's aims in terms of revenue and attendance. Indeed, offering a schedule of different prices according to seat location of the venue, is a practice that allows the theatre to discriminate customers according to their willingness to pay. This paper is a first attempt to develop a discrete choice model that analyze customers' preference of the attributes connected to the type of tickets, in terms of seat quality and day of performance.
We have employed a dataset that includes information on Royal Danish Theatre bookings in the period 2010-2013 with the aim to estimate three discrete choice models that explain

ticket purchase behaviour. Our analysis reveals how there are some distinguishable pattern that characterized the heterogeneous behaviour in the choice of theatre ticket. This heterogeneity in preferences is strictly connected to the customers' characteristics in terms of age and degree of frequency of theatre.
The result obtained aim to provide guidance to policy makers and theatre managers in setting prices. Indeed, price is one of the tool with which theatre can achieve their aims of increasing the theatre audience and the revenue from the box office.For example, a different pricing policy should be adopted for young and senior customers, as they exhibit the opposite pattern in terms of preference and willingness to pay. There is also room for the adoption of dynamic price, as the customers who buy the ticket in the end of the sale period are characterized by a higher price sensitivity. Our results suggest also to differentiate the pricing policy among production genres given that the customer's behaviour is not homogeneous among genres
Future studies could explore more in detail customer behaviour with respect to the price differentiation considering other socio-economic characteristics as income, education, family composition and so on. A further study on this topic is important, considering that the theatre demand has some peculiar features compared to other industries that adopt revenue management technique, as the transportation industries: a composite objective function that is not limited solely to revenue; the personal and subjective value of the cultural product, the lack of standardization of the product offered, and the risk component in the demand due to the unknown characteristics of the cultural product before its consumption.

References

[1] Abb-Decarroux, F. (1994). The perception of quality and the demand for services: Empirical application to the performing arts. *Journal of Economic Behavior & Organization*, 23(1), 99-107.

[2] Austen-SMith, D. (1980). On the impact of revenue subsidies on repertory theatre policy. *Journal of Cultural Economics*, 4(1), 9-17.

[3] Bliemer, M. C., Rose, J. M. (2013). Confidence intervals of willingness-to-pay for random coefficient logit models. *Transportation Research Part B: Methodological*, 58, 199-214.

[4] Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models. *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland.

[5] Bille, T. (2015). Theater Management - quality indicators and demand. *Paper presented paper presented at the The 13th International Conference on Arts & Cultural Management (AIMAC2015), June 29 July 1*, Aix-en-Provence / Marseilles, France.

[6] Boxall, P. C., Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: a latent class approach. *Environmental and resource economics*, 23(4), 421-446.

[7] Carrier, E. (2008). Modeling the choice of an airline itinerary and fare product using booking and seat availability data (*Doctoral dissertation, Massachusetts Institute of Technology, Department of Civil and Environmental Engineering).*

[8] Chan, T. W., Goldthorpe, J. H. (2005). The social stratification of theatre, dance and cinema attendance. *Cultural Trends*, 14(3), 193-212.

[9] Colbert, F., Beauregard, C., Valle, L. (1998). The importance of ticket prices for theatre patrons. *International Journal of Arts Management*, 1(1), 8-15.

[10] Corning, J., Levy, A. (2002). Demand for live theater with market segmentation and seasonality. *Journal of Cultural Economics*, 26(3), 217-235.

[11] Daly, A., Hess, S., De Jong, G. (2012). Calculating errors for measures derived from choice modelling estimates. *Transportation Research Part B: Methodological*, 46(2), 333-341.

[12] Drake, M. J., Duran, S., Griffin, P. M., Swann, J. L. (2008). Optimal timing of switches between product sales for sports and entertainment tickets. *Naval Research Logistics*, 55(1), 59-75.

[13] Felton, M.V. (1994). Evidence of the Existence of the Cost Disease in the Performing Arts. *Journal of Cultural Economics*, 18(4), 301-312.

[14] Fernandez-Blanco, V., Orea, L., Prieto-Rodriguez, J. (2009). Analyzing consumers heterogeneity and self-reported tastes: An approach consistent with the consumers decision making process. *Journal of Economic Psychology*, 30(4), 622-633.

[15] Greene, W.H., Hensher, D.A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research* B 37, 681-698.

[16] Grisola, J. M., Willis, K. G. (2011a). An evening at the theatre: using choice experiments to model preferences for theatres and theatrical productions. *Applied Economics*, 43(27), 3987-3998.

[17] Grisolia, J. M., Willis, K. G. (2011b). Heterogeneity In Willingness To Pay For Theatre Productions: Individual Specific Willingness To Pay Estimates For Theatres, Shows And Their Attributes. *Scottish Journal of Political Economy*, 58(3), 378-395.

[18] Grisola, J. M., Willis, K. G. (2012). A latent class model of theatre demand. *Journal of Cultural Economics*, 36(2), 113-139.

[19] Grisola, J. M., Willis, K. G. (2015). Consumer choice of theatrical productions: a combined revealed preferencestated preference approach. *Empirical Economics*, 1-25.

[20] Hansmann, H. (1981). Nonprofit enterprise in the performing arts. *The Bell Journal of Economics*, 341-361.

[21] Hetrakul, P., Cirillo, C. (2013). Accommodating taste heterogeneity in railway passenger choice models based on internet booking data. *Journal of choice modelling*, 6, 1-16.

[22] Horowitz, J., 1982. An evaluation of the usefulness of two standard goodness-of fit indicators for comparing non-nested random utility models. *Transportation Research Record* 874, 1925.

[23] Huntington, P. A. (1993). Ticket pricing policy and box office revenue. *Journal of Cultural Economics*, 17(1), 71-87.

[24] Kamakura, W. A., Russell, G. (1989). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research*, 26, 379-390.

[25] Krebs, S., Pommerehne, W. W. (1995). Politico-economic interactions of German public performing arts institutions. *Journal of Cultural Economics*, 19(1), 17-32.

[26] Laamanen J.P (2013). Estimating demand for opera using sales system data: the case of Finnish National Opera. *Journal of Cultural Economics* 37, 417-432.

[27] Lancaster K. J. (1966). A new approach to consumer theory. *The journal of political economy.*132-157.

[28] Leslie, P. (2004). Price discrimination in Broadway theater. *RAND Journal of Economics*, 520-541.

[29] McFadden, D. (1974). The measurement of urban travel demand. *Journal of public economics*, 3(4), 303-328.

[30] Roeder, K., Lynch, K. G., Nagin, D. S. (1999). Modeling uncertainty in latent class membership: A case study in criminology. *Journal of the American Statistical Association*, 94(447), 766-776.

[31] Rosen, S., Rosenfield, A.M. (1997). Ticket Pricing 1. *The Journal of Law and Economics*, 40(2), 351-376.

[32] Schimmelpfennig, J. (1997). Demand for ballet: a non-parametric analysis of the 1995 royal ballet summer season. *Journal of Cultural Economics*, 21(2), 119-127.

[33] Seaman, B. A. (2006). Empirical studies of demand for the performing arts. *Handbook of the economics of art and culture* 1, 415-472.

[34] Sintas, J. L., lvarez, E. G. (2005). Four characters on the stage playing three games: performing arts consumption in Spain. *Journal of Business Research*, 58(10), 1446-1455.

[35] Stigler, G. J., Becker, G. S. (1977). De gustibus non est disputandum. *The american economic review*, 67(2), 76-90.

[36] Swait, J. (1994). A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *Journal of retailing and consumer services*, 1(2), 77-89.

[37] Swanson, S. R., Davis, C., Zhao, Y. (2008). Art for arts sake? An Examination of motives for arts performance attendance. *Nonprofit and Voluntary Sector Quarterly*, 37, 300323.

[38] Tereyagoglu, N., Fader, P., Veeraraghavan, S. (2012). Filling seats at a theater: Estimating the impact of posted prices and dynamic discounts *Working paper, University of Pennsylvania, Philadelphia.*

[39] Throsby, D. (1990). Perception of quality in demand for the theatre. *Journal of Cultural Economics*, 14, 6582.

[40] Urrutiaguer, D. (2002). Quality judgements and demand for French public theatre. *Journal of Cultural Economics* 26, 185202.

[41] Vermunt, J. K., Magidson, J. (2005). Technical guide for latent GOLD choice 4.0. *Basic and Advanced, Belmont Massachusetts. Statistical Innovations Inc.*

[42] Wedel, M., Kamakura, W. A. (2000). *Market Segmentation: Conceptual and Methodological Foundations.* Dordrecht: Kluwer.

[43] Werck, K., Heyndels, B. (2007). Programmatic choices and the demand for theatre: The case of Flemish theatres. *Journal of Cultural Economics*, 31, 2541.

[44] Whelan, G., Batley, R., Shires, J., Wardman, M. (2008). Optimal fares regulation for Britains railways. *Transportation Research Part E: Logistics and Transportation Review*, 44(5), 807-819.

[45] Willis, K. G., Snowball, J. D. (2009). Investigating how the attributes of live theatre productions influence consumption choices using conjoint analysis: the example of the National Arts Festival, South Africa. *Journal of Cultural Economics*, 33(3), 167-183.

[46] Zieba, M. (2009). Full-income and price elasticities of demand for German public theatre. *Journal of Cultural Economics*, 33(1), 85108.

Appendices

A Productions considered in the models

Title	**Season**	**Genre**	**No. of performances**[a]
Et Folkesagn	2010/2011	Ballet	14
Boris Godunov	2010/2011	Opera	9
Madame Butterfly	2010/2011	Opera	16
Kvinden uden skygge	2010/2011	Opera	9
Balletaften	2010/2011	Ballet	10
Broadway for en aften	2011/2012	Ballet	14
Alceste	2011/2012	Opera	8
En skærsommernatsdrøm	2011/2012	Play	37
Così fan tutte	2011/2012	Opera	11
Kameliadamen	2011/2012	Ballet	13
Mågen	2011/2012	Play	27
Parsifal	2011/2012	Opera	10
Nøddeknækkeren	2011/2012	Ballet	18
Den Gerrige	2011/2012	Play	33
Albert Harring	2011/2012	Opera	9
Tannhäuser	2012/2013	Opera	10
Den fiffige lille ræv	2012/2013	Opera	11
Romeo & Juliet	2012/2013	Ballet	11
Madame Butterfly	2012/2013	Opera	19
Vildanden	2012/2013	Play	40
La Bayàdere	2012/2013	Ballet	14
Kollektivet	2012/2013	Play	26
La Ventana / Kermessen i Brügge	2012/2013	Ballet	8

[a] Performances with a flat price are excluded