Segmentation of Theatre Audience: Latent Class Approach

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Abstract: Theatrical productions are supposed to be perishable good, since the tickets for a particular play cannot be inventoried and sold after a time of play. In the revenue management of a perishable good price discrimination is widely used. Since the theatre audience is heterogeneous in terms of visit purpose, ability to perceive quality, willingness-to-pay, the strategy of price discrimination should be developed in the context of theatre segments. In this paper, we segment consumers of Perm Opera and Ballet Theatre, that allows to propose marketing instruments to increase theatre revenue. Since development of price discrimination strategy requires data on consumer's purchase history, his behavioral and socio-demographic characteristics, we combine two data sources: data on ticket purchases and data obtained from survey. Latent class logit model allows to identify different segments of the theater's audience. The study reveals theatregoers segments with different willingness-to-pay for performance and seat location characteristics, which allows developing detailed recommendations on the pricing strategy for various theater audiences.

Keywords: theatre, preferences, segments, willingness-to-pay

JEL: Z11, C53, D12

1. Introduction

Theatrical productions are supposed to be specific economic goods. They possess the features that characterize the perishable goods (Choi, Jeong & Matilla, 2014; Ozhegov & Ozhegova, 2017). According to Hetrakul and Cirillo (2014) the definition of perishable good includes some special aspects. The key aspect of a perishable good is that tickets for a particular play cannot be inventoried and sold after a time of play. Inflexible capacity is implicated by the limited number of seats in a house. Variable and uncertain demand assumes that the attendance

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on a particular performance depends on the day of week, the time of day and the season as well as on the characteristics of production. The cost of production creation is high due to significant fixed costs on decorations, costumes, director reward, etc. Whereas marginal cost of a particular performance is much lower as marginal cost of additional attendee. These product's features prove the need for a particular approach to charge the prices.

In fact, the methods of price discrimination are widely used in the management of a perishable good demand. By virtue of the fact that theatre audience is heterogeneous in terms of visit purpose, ability to perceive quality, willingness-to-pay for performance and seat. Furthermore, theatrical production is a highly differentiated product, that possess a number of performance and play characteristics and the seats in the house vary by the distance to the stage, the quality of view and sound and, finally, by price. Considering these features of product and consumers, the theatre with heterogeneous consumers and differentiated performances and seats has an ability for ticket price discrimination.

Policy of price discrimination is based on the idea that a ticket price is charged depending on the consumer willingness-to-pay for a product. Price elasticity is a fundamental concept in estimating willingness-to-pay. As a result, price elasticity for theatre demand has been a subject of detailed examination for decades (Moore, 1966; Houthakker & Taylor, 1970; Touchstone, 1980; Gapinski, 1984; Bonato, Gagliardi & Gorelli, 1990; Zieba, 2009). Summarizing the findings, one may conclude that the demand for theatre performances is weakly elastic by price but the estimate of elasticity varies substantially.

While a consumer demands for theatrical production characteristics, purchasing the ticket he also pays attention to the seat in a house. In contrast, previous studies principally model the demand for performances. There are few studies where authors consider the demand for a particular seat in a house (Schimmelpfennig, 1997). In this paper, we study demand in great depth considering the attendance of particular seats in a house.

The idea of exploring demand in the context of seats in a house is supported by the need to account for cross-price elasticity. When the administration increases the price for a ticket, the consumer may refuse from theatre visit or may switch to another seat in a house with a different price. To perform price discrimination policy, theatre administration should recognize the patterns of cross-price elasticity between seats in a house. This allows to understand how the consumers will react to a ticket price change. The issue of cross-price elasticity between different seats has been poorly investigated in the literature. This emphasizes the scientific novelty of this paper.

Apparently, theatre audience differs by performance and seat preferences and willingness-to-pay for performance and seat characteristics. Therefore, we consider that estimates of price elasticity allow to reveal different consumer groups, so that theatre visitors within the group are homogeneous in terms of price sensitivity, while consumers between groups remain heterogeneous. Detection of consumer segments in such a manner leads to fine-tuning of pricing strategy with respect to theatre revenue. Thus, we aim this study to reveal theatre segments and develop marketing tools for various theatre segments to increase theatre revenue.

In this paper, we study consumers of Perm Opera and Ballet Theatre, one of best regional musical theatre in Russia. We employ data on online ticket purchases. Since the purchase goes through the theatre website, we observe information identifying a consumer, such as name and email. This allows to follow up the history of spectator' attendance including frequency, price of bought tickets, location of bought seats in a house and attended performances.

At the same time, the actual data about consumer behavior do not permit to study cross-price elasticity within the seats in a house, since current pricing policy of the theatre assumes simultaneous proportional price change for the seats in the house. This leads to the problem of price multicollinearity and underidentification of cross-price elasticity. Data on internet purchases also lack sociodemographic consumer characteristics. Absence of consumer characteristics does not allow to describe consumer segments. Thus, actual data on tickets sales allow to study real behavior of theatre audience, but make an identification of cross-price elasticity patterns impossible.

Along with the data on actual consumer choice we collect survey data. Since we have a database with consumer emails, we conduct email-based online survey. The part of survey is devoted to the discrete choice experiment, where the respondent is set in a hypothetical situation of choice. As we mentioned earlier, the challenge working with actual sales data in the theatre is an absence of price variation within the same price scheme. The choice experiment permits to induce variation in the price and avoid the issue of price multicollinearity. The inclusion of survey data also makes the dataset richer adding the consumer characteristics. This allows to obtain insights about consumer segments and its preferences towards seats in a house and performance characteristics.

Having data from sales system and surveys we combine these two types of data. Data combination allows to avoid shortcomings of each data source and incorporate benefits. Combination of datasets in this study allows to estimate price elasticity of demand, segment theatre audience, describe the groups in terms of socio-demographic and behavioral characteristics and propose recommendations for working with these consumer groups (Needleman, 1976).

In order to identify consumer utility from ticket purchase we employ the class of discrete choice models (DCM). These models decompose utility to parts related to the production and play characteristics, utility gained from a chosen seat and disutility from ticket price. Estimation of utility function parameters permits to estimate sensitivity to a price change, willingness-to-pay for a particular seat and certain performance characteristic. Particular class of DCM, latent class model, allows to identify consumer segments by their preferences, describe them by consumer characteristics and provide marketing tools for influencing different consumer groups.

The rest of the paper is organized as follows. The next part outlines the literature devoted to the theatre demand. It is followed by the section explaining the data. The methodology is discussed in the next section. Section with expected results is concluded.

2. Literature review

2.1. Literature on theatre demand

The empirical literature on theatre demand modelling has evolved since 1960s. In early studies the demand was considered mainly as a function of price (Moore, 1966). More sophisticated models included the product characteristics, such as repertory classification, the author, the standard of performance (Throsby, 1990). Particular discussion in the literature was dedicated to the issue of quality assessment in the demand model (Throsby, 1990; Abbe-Decarroux, 1994; Withers, 1980). They conclude that the perception of quality ex-ante is an important determinant for consumer that seeking information before ticket purchase. Then the demand model depends on observable characteristics for a consumer, such as the type of play, the author, awards, etc.

In terms of data collection there are two basic approaches – stated and revealed preferences. Revealed preferences approach is based on what consumers actually do. In other words, it employs real data about purchases. Stated preferences approach is used when the real data are absent or the survey is the only way to identify the research phenomenon. Papers based on revealed preferences have distinctions in the level of data aggregation. The majority of earlier papers uses data aggregated to year or season level, region, company or venue level (Houthakker & Taylor, 1970; Touchstone, 1980; Gapinski, 1984; Bonato, Gagliardi & Gorelli, 1990). Employing aggregated data may affect the results of estimation due to averaged values of variables. Recent studies use more detailed data on theatre attendance. For example, data aggregated by productions or particular performances. Use of disaggregated data permits to make more detailed conclusions about behavior patterns among consumers (Ozhegov & Ozhegova, 2018). The development of discrete choice models forwards the issue of demand estimation making the demand modelling using individual data possible.

In the context of revealed preferences approach, it is worth noting that demand has different measures, such as the revenue from tickets sale, the number of tickets sold per year or month, the number of tickets sold per performance or the share of tickets sold in a house. In the process of demand modelling, some of the demand measures may pose a difficulty related to the limited capacity of a house. In the literature, this problem is called censorship of data. In this case, the number of tickets sold for the performance is the only observed demand, while potential demand may exceed the capacity of a house. Dropping the distinction between potential and observed demand may affect the estimates of parameters and lead to the bias. In early papers authors employ the simplest approaches dealing with censored data: to ignore the fact of data censorship or to exclude the censored observations from the sample. Some papers include house capacity as explanatory variable in the model in an attempt to take into account the demand censorship. In other field of demand modelling the authors solve the problem of censored data analysis using Tobit model, EM method, or different assumptions on censored demand distribution. In the context of theatre demand, Laamanen (2013) model latent demand using censored quantile regression, which allows the dependent variable to be censored (Lévy-Garboua & Montmarquette, 2003).

Another group of studies uses individual survey data. Demand studies that employ individual-level data are able to get estimates on the effects of audience characteristics. The authors have done an extensive work concerning revealing of customer segments among theatre audience (Baumol & Bowen, 1966; Colbert & Nantel, 1989). Survey data also permit to estimate customer's willingness-to-pay for different attributes (Levy-Garboua & Montmarquette, 1996; Hansen, 1997; Schulze & Rose, 1998; Grisolia & Willis, 2012).

Studies employing individual survey data usually employ discrete choice models that are based on Random Utility Theory (Lancaster, 1966). This is the theory of consumer demand where the utility of a good depends on the attributes and stochastic term. Then the consumer choses the variety maximizing his utility. Multinomial (MNL) or binary logit are the simplest models to estimate the consumer's utility from a product (Favaro & Frateschi, 2007; Willis & Snowball, 2009; Grisolia & Willis, 2011). In papers with ordered dependent variables authors employ a special case of multinomial logit – ordered logit (Hansen, 1997; Morey & Rossmann, 2003; Favaro & Frateschi, 2007; Willis & Snowball, 2009; Grisolia & Willis, 2011). This method is used for models with interval latent dependent variable such as willingness-to-pay. The weakness of MNL models includes the inability to account for unobserved consumer heterogeneity. There is a more general model that overcomes the blind side of multinomial logit. A mixed logit (MXL) model introduces the variation in parameters estimating the distribution of consumers' tastes (Grisolia & Willis, 2015). The special case of a mixed logit is a latent class model, where the distribution of utility parameters is discrete and consumers are segmented into the discrete groups with homogeneous tastes (Grisolia & Willis, 2012).

Both revealed and stated preferences approaches have strengths and weaknesses. Method of revealed preferences is based on real purchase behavior of consumer, that is, definitely, an advantage of this method. However, there is a challenge with RP data if the attributes of a product are not separable. Insufficient variation in data may lead the impossibility of all parameters identification. Stated preferences approach can solve this problem using discrete choice experiments, so that small volume of sample may ensure sufficient variation in data. Combining RP decisions made at real conditions and SP choices made under hypothetical conditions can aid to overcome the mutual shortcomings of the approaches and consolidate the strengths. Choice experiments address the issue of insufficient variation in attributes, the data on real behavior induce realism into the model. In the paper (Grisolia & Willis, 2015) the authors demonstrate the advantages of combined RP-SP data method in identifying the consumer preferences for performance characteristics.

In this article, we focus on the model of individual choice in the theatre using the joint RP and SP data approach proposed by (Grisolia & Willis, 2015). RP data permit to account for real behavior of consumer. The data from sales system do not have information on consumers apart from their behavior in past. The inclusion of SP data provides socio-demographic information on consumers. Applying of choice experiments overcomes the problem of insufficient variation in attributes and multicollinearity in prices. Having rich data on customers, their preferences obtained from their past history of purchases and choices in hypothetical conditions, we may reveal customer segments. We contribute to the literature by finding the preferred seats in a house for each segment, and patterns of switching for the segments depending on the performance characteristics.

1.2 Literature on experimental design

In the context of SP data collection approach there are stated choice experiments that are mostly used for estimation and prediction of consumer behavior. This kind of experiments rely on underlying experimental designs. This part of literature review gives an overview of the steps for generating stated choice experiments (Rose & Bliemer, 2006; Rose & Bliemer, 2007).

The purpose behind generating stated choice (SC) experiment is to determine the effect of different attributes on observed choice made in an experiment. The allocation of attribute levels over the choice sets has a key role in an experiment and influences the statistical power of models estimated on these data. Typically stated choice experiments consist of numerous respondents being asked to complete a survey with a choice in a number of choice occasions (choice sets) where they are asked to choose one alternative from a discrete set of alternatives (Rose & Bliemer, 2009; Bliemer & Rose, 2010).

SC experiment is determined by a number of features. First of all, SC experiment may be labelled, when alternatives are marked by names with substantive meaning to the respondent, or unlabelled, when the names of alternatives reflect, as an example, their relative order of appearance). The distinction between labelled and unlabeled experiments is that labelled experiments require to estimate alternative specific parameters (Rose & Bliemer, 2012).

The second feature of SC experiment is attribute level balance, which requires each level of attribute to be presented an equal number of times. This property is desirable, since ensures necessary range of levels for effective parameters estimation, but not obligatory (Kanninen, 2002). Moreover, attribute balance property may restrict the design to be optimal for some criterion (Rose & Bliemer, 2009).

Next feature of stated choice experiment is the number of attribute levels. In the case of continuous variable the number of attribute levels is given by model specification. The wide attribute level range is statistically preferable than narrow range, since wide range results are more effective. The number of levels is predetermined, if the attribute is coded as a number of dummies.

Finally, when the attributes and attribute levels are chosen, we are able to generate experimental design. Full factorial design includes all possible choice situations. Practically the number of all possible choice situations is too large. Therefore, the researchers use fractional factorial design – subset of choice situations. The procedure of generating choice situations in fractional factorial designs is the same. The analyst starts from generating the full factorial design, then take a subset of choice situations relying on the certain criterion of optimality. Random factorial design is a possible way of choosing choice situations, but expectedly not the best. Orthogonal design is one of the best known type of choosing a choice situations subset. Taking a situation in final design it tries to minimize the correlation between characteristics in the choice situations. There is a number of reasons to use an orthogonal design. It is easy to construct, convenient for linear models, allows to independently evaluate the parameters of characteristics. However, the minimization of correlation between attributes does not ensure the effectiveness of estimation. Hence, recently researchers have suggested another type of factorial design – efficient design. This type of fractional factorial design is aimed to maximize the information extracted from each choice situation. Technically, it seeks for design with efficient estimates in terms of predicted standard errors of resulting parameters (Sándor & Wedel, 2001; Sándor & Wedel, 2002; Sándor & Wedel, 2005).

Traditionally efficient designs require prior knowledge about asymptotic variance-covariance (AVC) matrix. Priors allow to better distribute attribute levels in the design. Prior knowledge may come from previous literature, pilot studies and theory of consumer behavior.

Within the literature there are a number of measures used as a criterion of efficiency (Rose & Bliemer, 2009; Rose et al., 2008; Kessels et al., 2006). However, there is one the most predominantly used measure – D-error statistic. This criterion is calculated as a determinant of AVC matrix. Therefore, the designs that minimize the D-error statistic are called D-efficient designs.

More recently researchers have begun to use designs without prior parameters about AVC matrix. In these cases, prior parameters are drawn from Bayesian parameter distribution. Bayesian efficient designs get rid of necessity to make priors and, consequently, are robust to errors in prior settings (Ferrini & Scarpa, 2007).

Since there is no previous research based on the consumer behavior data from Perm opera and ballet theatre then no prior information about the distribution of parameters is available. In this research we use Bayesian D-efficient design to construct choice experiment that is efficient resulting parameters estimates and robust to the choice of prior for the parameters (Falke & Hruschka, 2017).

3. Methodology

Both RP and SP approaches for identification of consumer preferences are based on random utility theory (Lancaster, 1966). It states that utility for a certain consumer is determined by characteristics of a good. As an econometric model, utility function is decomposed on a deterministic component that depends on the observed characteristics of a product and a random (unobserved) component. Then utility function may be written as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = x_{ijt}\beta + \varepsilon_{ijt}, \quad (1)$$

where V_{ijt} is a deterministic part of utility of a consumer i from an alternative j in a choice situation t, x_{ijt} is a vector of observed variables (price and product characteristics), β is a vector of taste parameters to be estimated, ε_{ijt} is an unexplained by the observable characteristics part of the utility.

To estimate the taste parameters a consumer is considered as a rational individual that maximizes her utility and some form of random component distribution is assumed. If the random component is *i.i.d.* (independently and identically distributed) from $EV\ I$ (Gumbel) distribution with variance normalized to 1, the model takes a form of Multinomial Logit (MNL). According to McFadden (1974), the probability that a consumer i chooses the alternative j in a choice situation t in MNL model is:

$$P_{ijt} = \frac{\exp(x_{ijt}\beta)}{\sum_q \exp(x_{iqt}\beta)}. \tag{2}$$

Estimation of multinomial logit model is performed using maximum likelihood method where density of choice is a density of multinomial distribution. If y_{ijt} is an indicator of choice of alternative j by individual i in a choice situation t then the likelihood function may be written as:

$$L(y, x|\beta) = \prod_i \prod_t \prod_j {P_{ijt}}^{y_{ijt}}. \tag{3}$$

Maximization of (log)likelihood function with respect to taste parameters β leads to an identification of utility function parameter up to a parameter of error variance. Whereas multinomial logit allows to model customer choice, it places restrictive assumption on model causing estimated parameters to be the same for the whole population. This assumption seems unrealistic, since considers the tastes among population to be homogeneous. The need to account for consumer heterogeneity has led to development of following models.

There are two ways to weaken the assumption about consumer homogeneity. The first approach models heterogeneity in tastes through the difference in socioeconomic characteristics (often named systematic heterogeneity). To account for systematic heterogeneity in MNL model, one may include sociodemographic variables multiplied by product attributes to study the differences in taste parameters between segments of population (male and female, with and without children, etc.) (Ortuzar & Willumsen, 2001).

The second approach is dedicated to modelling non-systematic or unobserved heterogeneity in tastes across consumers. This approach allows to model heterogeneity that is not explained by observable consumer characteristics, such as gender, age, education, etc. The model implies that each respondent has its own parameters of utility function, that is why the model is called as mixed logit (MXL). The specification of model is similar to the MNL:

$$U_{ijt} = x_{ijt}(\beta + v_i) + \varepsilon_{ijt} = x_{ijt}\beta_i + \varepsilon_{ijt}, \tag{4}$$

where: β_i is the attribute preferences of individual i, that deviates from the average preferences, β is the average attribute preferences, υ_i is the deviation of individual taste parameter from the average population on that is taken from distribution $f(\cdot)$. Then mixed logit choice probability can be expressed in the form of multidimensional integral of logit probability over a distribution of tastes:

$$P_{ijt} = \int \frac{\exp(x_{ijt}\beta_i)}{\sum_q \exp(x_{iqt}\beta_i)} df(\beta_i), \tag{5}$$

where $f(\cdot)$ is a joint density function of individual tastes.

Assuming consumer heterogeneity mixed logit model allows to obtain the parameters of distribution for taste estimates for the whole population but not for a particular consumer. From the point of view of marketing strategies this model does not permit to propose instruments of influence, therefore in the study we focus on a special discrete case of MXL – latent class model (LCM).

Latent class as MXL model deals with consumer heterogeneity, but in this model the population is segmented into discrete classes with a specific vector of parameters for each class. Latent class model may be presented as a sum of MNL models adjusted for the mass of each class, then the probability of choice is expressed by a sum of conditioned probabilities weighted by the probability of belonging to each class (the size of class in population):

$$P_{ijt} = \sum_m S_{im} \frac{\exp(x_{ijt}\beta_m)}{\sum_q \exp(x_{iqt}\beta_m)}, \tag{6}$$

where S_{im} is the probability of individual i to belong to the class m.

S_{im} is also a function from observed consumer characteristics:

$$S_{im} = P(class_i = m) = \frac{\exp(d_i\gamma_m)}{\sum_s \exp(d_i\gamma_s)}, \tag{7}$$

where d_i is a vector of socio-demographic characteristics, γ_m are the parameters of class membership model, m is a latent class.

This allows to model a probability of consumer membership to a certain class and describe classes in terms of their socio-demographic characteristics. The probability of belonging to a class S_{im} also takes a form of multinomial logit:

$$P_{ijt} = \sum\nolimits_m \frac{\exp(d_i\gamma_m)}{\sum_s \exp(d_i\gamma_s)} \frac{\exp\left(x_{ijt}\beta_m\right)}{\sum_q \exp(x_{iqt}\beta_m)}. \tag{8}$$

The likelihood function for LCM is similar to eq. (3) but is maximized according to both taste parameters β and class membership parameters γ. Typically a problem of finding a global maximum is solved by maximization of likelihood function with respect to both β and γ simultaneously. Since this approach is usually cumbersome by virtue of complex structure of an objective function and presence of multiple maxima, we apply EM algorithm with a sequential iterative maximization of parameters β and γ in equation (8). This procedure works expectedly slower compared to previous way and provide less efficient estimates but leads to proper estimates more often.

Since the processes of generating of RP and SP data differ from each other, utility functions also have some differences. Given the knowledge about the source of data we may write an equation (1) for different data structure. Making an assumption that a consumer chooses a seating area within a particular play of production (in RP data an alternative is seating area) we may rewrite utility function for RP data as:

$$U_{ijt}^{RP} = x_{jt}^{RP}\beta^{RP} + x_t^{RP}\theta_j^{RP} + \alpha \ln p_{jt} + \mu_j + \varepsilon_{ijt}^{RP}, \tag{9}$$

where U_{ijt}^{RP} is a utility function that explains a choice of alternative j by consumer i in a real choice situation t, x_{jt}^{RP} are characteristics that vary across alternatives within a choice set (percent of sold tickets in a seating area in RP data), x_t^{RP} are characteristics that describe a choice situation but not an alternative (characteristics of performance and play in RP data), $\ln p_{jt}$ is a log. of ticket price, μ_j is an alternative (seating area) specific constant, ε_{ijt} - Gumbel distributed error term.

Whereas the experiment of discrete choice is designed to repeat the situation of real ticket choice, it has some peculiarities that differ utility function for SP data. It has the same form as for RP but differs in a set of attributes:

$$\begin{gathered} U_{ijt}^{SP} = x_{jt}^{SP}\beta^{RP} + \alpha \ln p_{jt} + \mu_j + \varepsilon_{ijt}^{SP} \\ U_{i0t}^{SP} = \mu_0 + \varepsilon_{i0t}^{SP}, \end{gathered} \tag{10}$$

where: U_{ijt}^{SP} is a utility function that explains a choice of consumer i from alternative j in a choice situation t, x_{jt}^{SP} is characteristics which vary across alternatives within a choice set (characteristics of performance).

Zero index for alternative represents an option to choose none of proposed alternatives in a particular choice set. This alternative contains no observed characteristics which may explain a choice, has zero log of price and alternative specific constant μ_0.

Despite the differences in data generating process utility functions which explain an individual's choice in RP and SP choice situations have similar structure and common subset of parameters (price elasticity and alternative specific constants). The set of common parameters may be identified from both sets of data, while the rest of the parameters may be identified from either RP or SP data.

For identification of common parameters one should account for parameters estimates normalized to the variance of error term. When the true variance of error term in utilities given in (9) and (10) are underidentified, matching of RP and SP and joint identification of common parameters requires scaling of SP (or RP) part to a parameter ρ. Scale parameter reflects the ratio between the true but unobserved ratio of error variances between RP and SP data. Generally, this ratio is unequal to 1, because of different set of regressors explaining RP and SP choices and usually more noisy SP data (Morikawa, McFadden, Ben-Akiva, 2002).

If ρ is known or estimated, then the structure of utility function for join RP and SP choice may be represented as:

$$\begin{cases} U_{ijt}^{RP} = x_{jt}^{RP}\beta^{RP} + x_t^{RP}\theta_j^{RP} + \alpha \ln p_{jt} + \mu_j + \varepsilon_{ijt}^{RP} \\ \rho U_{ijt}^{SP} = \rho(x_{jt}^{SP}\beta^{RP} + \alpha \ln p_{jt} + \mu_j + \varepsilon_{ijt}^{SP}) \\ \rho U_{i0t}^{SP} = \rho\big(\mu_0 + \varepsilon_{i0t}^{SP}\big), \end{cases} \tag{11}$$

where ρ is a ratio between RP and SP error variances.

Then one may estimate a full set of parameters of multinomial logit type of model (11) under assumption of heteroscedastic across types of data $EV\ I$ distribution of joint error ε_{ijt}. According to an equation (2) probabilities of observed choice may be written for RP and SP data separately as:

$$
\begin{aligned}
P_{ijt}^{RP} &= \frac{\exp(x_{jt}^{RP}\beta^{RP} + x_t^{RP}\theta_j^{RP} + \alpha \ln p_{jt} + \mu_j)}{\sum_q \exp(x_{qt}^{RP}\beta^{RP} + x_t^{RP}\theta_q^{RP} + \alpha \ln p_{qt} + \mu_q)} \\
P_{ijt}^{SP} &= \frac{\exp(\rho(x_{jt}^{SP}\beta^{SP} + \alpha \ln p_{jt} + \mu_j))}{\exp(\rho\mu_0) + \sum_q \exp(\rho(x_{qt}^{SP}\beta^{SP} + \alpha \ln p_{qt} + \mu_q))}.
\end{aligned} \tag{12}
$$

Given the probabilities of choice the model (12) may be estimated *via* full information maximum likelihood (FIML) for the likelihood function in the following form:

$$
L(y, x, p|\beta, \theta, \alpha, \mu, \rho) = \prod_i \prod_{t \in RP} \prod_j \left(P_{ijt}^{RP}\right)^{y_{ijt}} \prod_{t \in SP} \prod_j \left(P_{ijt}^{SP}\right)^{y_{ijt}}. \tag{13}
$$

The maximization of likelihood function (13) requires a pre-step of scale parameter ρ estimation. In order to estimate a scale parameter the following algorithm is applied (Swait & Louviere, 1993):

1. Draw B bootstrap samples of all individuals in RP data. For each bootstrap sample b estimate ξ_b^{RP} that is a set of RP-identified parameters $\beta_b^{RP}, \theta_b^{RP}, \alpha_b^{RP}, \mu_b^{RP}$ maximizing RP part of (12) only. Thus, we obtain B collections of RP parameters ξ_b^{RP}.
2. Draw B bootstrap samples of all individuals in SP data. For each bootstrap sample b estimate ξ_b^{SP} that is a set of SP-identified parameters $\beta_b^{SP}, \alpha_b^{RP}, \mu_b^{RP}$ maximizing SP part of (12) only. Thus, we obtain B collections of RP parameters ξ_b^{RP}.
3. On collections of RP and SP estimated parameters obtained from bootstrap samples one may estimate ρ by OLS from the equation:

$$
\xi_b^{RP} = \rho \xi_b^{SP} + \eta_b, \tag{14}
$$

where η_b is *i.i.d.* error vector.

In order to identify and describe consumer segments we generalize choice model (11) for the case of latent classes presence. Let d_i^{RP} be a set of behavioral consumer characteristics available from RP data and d_i^{SP} be a set of socio-demographic characteristics available from SP data, I_i^{RP} and I_i^{SP} be the indicators of RP and SP data collection respectively for individual i, then the probability of individual's i membership to latent class m under logit assumption may be represented as:

$$S_{im} = [\frac{\exp\left(d_i^{RP}\gamma_m^{RP} + \left(1 - I_i^{SP}\right)\kappa_m^{RP}\right)}{\sum_s \exp\left(d_i^{RP}\gamma_s^{RP} + \left(1 - I_i^{SP}\right)\kappa_s^{RP}\right)}]\left(1 - I_i^{SP}\right) + [\frac{\exp\left(d_i^{SP}\gamma_m^{SP} + (1 - I_i^{RP})\kappa_m^{SP}\right)}{\sum_s \exp\left(d_i^{SP}\gamma_s^{SP} + (1 - I_i^{RP})\kappa_s^{SP}\right)}](1 - I_i^{RP}) + [\frac{\exp\left(d_i^{RP}\gamma_m^{RP} + d_i^{SP}\gamma_m^{SP}\right)}{\sum_s \exp\left(d_i^{RP}\gamma_s^{RP} + d_i^{SP}\gamma_s^{SP}\right)}]I_i^{RP}I_i^{SP}, \tag{15}$$

where γ_m^{RP} and γ_m^{SP} are contribution of observed RP and SP consumer's characteristics to the probability of i-th individual's membership to a class m, κ_m^{RP} and κ_m^{SP} are contribution of RP and SP data if it is unobserved.

Equation (15) models a probability of belonging to a class m for the three possible cases. The first term of sum makes a contribution to the membership probability if only RP data for individual i is observed. The second term of sum makes a contribution to the membership probability if only SP data for individual i is observed. The last term makes a contribution to the membership probability if both RP and SP data for individual i are observed. If $\beta_m, \theta_m, \alpha_m, \mu_m$ are parameters of choice model (11) utility function for an individual belongs to a class *m*, then choice probabilities for an individual i may be written as:

$$\begin{aligned} P_{ijt}^{RP} &= \sum_m S_{im} \frac{\exp(x_{jt}^{RP}\beta_m^{RP} + x_t^{RP}\theta_{jm}^{RP} + \alpha_m \ln p_{jt} + \mu_{jm})}{\sum_q \exp(x_{qt}^{RP}\beta_m^{RP} + x_t^{RP}\theta_{qm}^{RP} + \alpha_m \ln p_{qt} + \mu_{qm})}, \\ P_{ijt}^{SP} &= \sum_m S_{im} \frac{\exp(\rho(x_{jt}^{SP}\beta_m^{SP} + \alpha_m \ln p_{jt} + \mu_{jm}))}{\exp(\rho\mu_{0m}) + \sum_q \exp(\rho(x_{qt}^{SP}\beta_m^{SP} + \alpha_m \ln p_{qt} + \mu_{qm}))}. \end{aligned} \tag{16}$$

The full set of model parameters may be obtained by EM algorithm of full information likelihood function (Hensher & Bradley, 1993):

$$L(y, x, p|\beta, \theta, \alpha, \mu, \gamma, \kappa, \rho) = \prod_i \prod_{t \in RP} \prod_j \left(P_{ijt}^{RP}\right)^{y_{ijt}} \prod_{t \in SP} \prod_j \left(P_{ijt}^{SP}\right)^{y_{ijt}}. \tag{17}$$

4. Data collection

Data for this research were collected from people attending plays in Perm Opera and Ballet Theatre, which is considered as one the best regional opera theatres in Russia. It is famous for its modern musical productions, nonstandard classical performances, and unconventional festival projects. It is also a major Russian center for opera and ballet, where the quality of the musical performance is paramount. The theatre represents around 200 shows per year, 40 from which are unique productions and 3-5 new productions per year.

Perm Opera and Ballet Theatre is a non-commercial organization and as such is loss-making. As of 2016, Perm state budget covers around 75 percent of expenses, 17 percent comes from income from ticket sales, and, finally, 8 percent is covered by sponsorship. As a non-commercial venture the goal of the theatre is to make ballet and symphonic art available for Perm residents. The theatre does have to, at least partially, recoup the expenses with production revenue in order to produce new ones. Consequently, the theatre constantly tries to balance between being affordable and covering costs using pricing mechanism and charging different prices for different performances and seats.

In order to analyze preferences of Perm opera and ballet theatre consumers we collect the data from two main sources which are described below.

4.1. RP data

RP data are taken from sales system of the theatre. Dataset includes information on tickets purchase for six seasons between August 2011 and July 2017. During this time the Perm theatre has shown 966 plays of 160 unique productions. Since the shows that the theatre performed are highly differentiated, that is embodied in various types of shows and pricing strategies for these shows, for analysis purposes the study focuses on performances that in a sense are homogeneous. This requires the imposition of certain restrictions.

The house of theatre is divided into 11 seating areas according to the distance to the stage (Figure 1). The seats in different seating areas vary by the quality of view and sound, prestige and, consequently, by price (Figure 2). Whereas the seats located in one seating area are considered as roughly homogeneous in terms of price and quality. Thus, the seat in a house is identified through a seating area, a row and a place. Besides, the house of the theatre has some ways to be divided into seating areas. Luckily, there is one scheme of theatre house decomposition that covers around 70 percent of performances and brings 90 percent of total revenue. The analysis in the paper is focused on performances with this scheme of theatre decomposition that ensures the homogeneity in data collected.

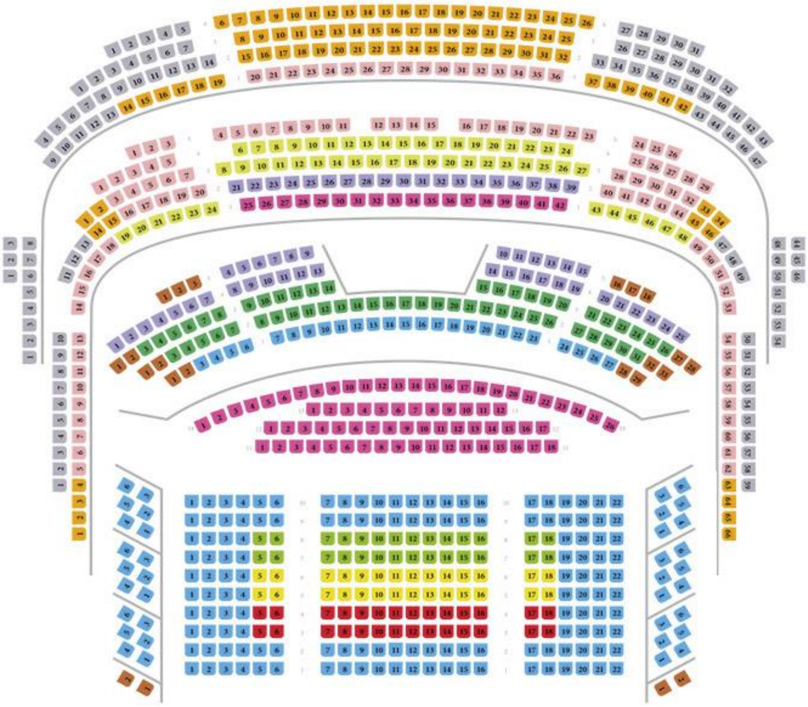

Figure 1. Scheme of a house

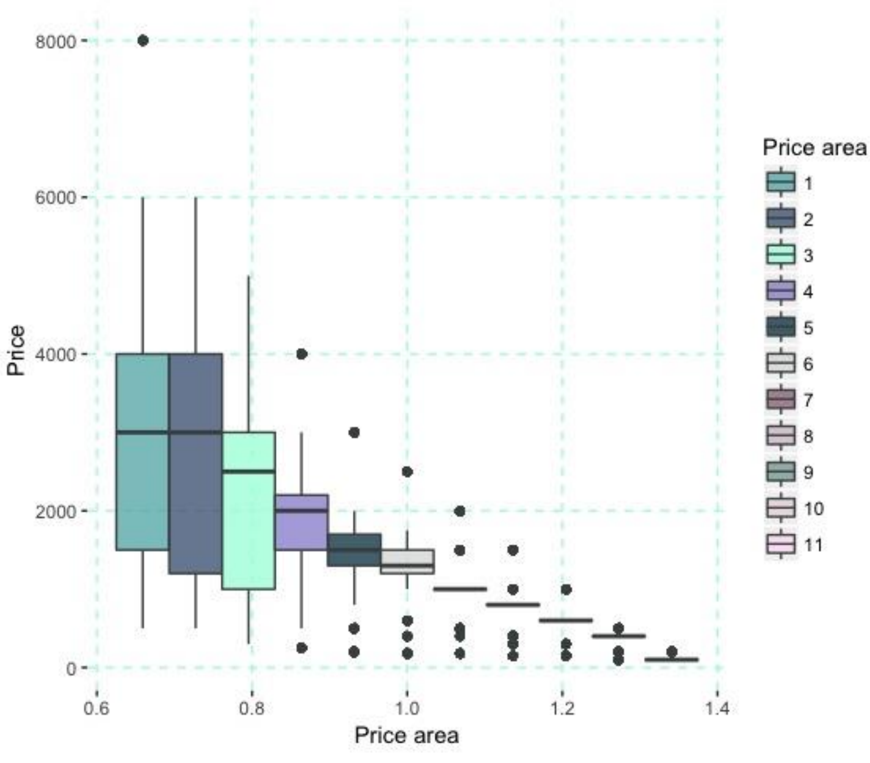

Figure 2. Distribution of ticket price across seating areas

The theatre mostly shows productions at the main venue of house. However, some specific performances require particular conditions. In that cases the tickets are sold in the hall of building or behind the scenes. At times the theatre company goes on tour, where perform plays in tour halls. In this paper, we confine our analysis to the plays that have been showed at the main venue of Perm house.

Moreover, the study includes for consideration only operas and ballets, since these types of shows possess similar set of characteristics that allow to estimate the contribution of a particular performance attribute. Thus, given these limitations RP data include information for 210 plays, 40 of which are unique productions.

For plays included in the analysis we collect information on performance characteristics which explains the demand according to previous research (Seaman, 2006). We classify productions into operas and ballets, into classical (written before 1900) and modern (written after 1900) ones, include information on the author and construct dummy responsible for the nationality of the author (Russian/foreign) and the dummy on whether the production is a premiere one (Laamanen, 2013). We classify performances according to the age recommended for attendance: children (without restriction), family (12+) and adult (16+). Information on conductors allows estimating the contribution of a particular person. Among conductors, we identify three persons that are especially successful and in-demand (Urrutiaguer, 2002; Willis and Snowball, 2009). Perm Opera and Ballet Theatre has been regularly nominated for the prestigious Russian theatre award “Golden Mask”. For each production, we collect information on the number of nominations and awards won. In order to measure the world popularity of musical composition, we add the data on various ratings (Felton, 1989). We use data from the worldwide rating of operas and their composers (operabase.com) and of ballets (listverse.com). Table 1 represents descriptive statistics for performance characteristics. It is seen that 45 percent of performances are ballets, the rest 55 percent are operas. 61 percent of plays demonstrated are operas or ballets that are included in the rating of best operas or ballets respectively. A fifth of plays has at least one nomination in Golden Mask Prize (Buzanakova & Ozhegov, 2016).

There are two main ways that customers use to purchase the tickets: through booking office and website of the theatre. Consumer regardless of the sales channels face the same set of available seats. Booking office is located near the theatre, and someone may have challenges with getting to the place. For convenience, the theatregoers have possibility to buy the tickets through the theatre website. Currently, almost 50% of purchases is carried out online and the proportion steadily grows. In the study, we focus on online purchases, since these transactions store the information not only about the tickets bought, but also about the buyer, at least his email address. Regardless of sales channel consumer has the same set of available tickets, there is no challenge with choice set recovery.

Table 1. Descriptive statistics for performance characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
Ballet	210	0.45	0.50	0	1
Top 10 rated opera	210	0.10	0.31	0	1
Top 100 rated opera	210	0.08	0.27	0	1
Top 10 rated ballet	210	0.43	0.50	0	1
Balletmeister: Miroshnichenko	210	0.24	0.43	0	1
Choirmeister: Polonskiy	210	0.17	0.38	0	1
Conductor: Abashev	210	0.18	0.39	0	1
Conductor: Platonov	210	0.43	0.50	0	1
Conductor: Currentzis	210	0.21	0.41	0	1
Golden Mask Laureat	210	0.21	0.41	0	1
Weekend	210	0.56	0.50	0	1
High season	210	0.69	0.46	0	1
Premiere of season	210	0.17	0.37	0	1

Table 2 exhibits descriptive statistics for online and offline purchases. It is seen that offline and online buyers demonstrate different preferences related to performance characteristics. Thus, online buyers prefer more to attend ballets rather than operas, plays with nominations in Golden Mask, more often visit plays with Currentzis as a conductor and premiere plays. Online buyers buy the tickets 32 days before the performance in average that is less than for offline buyers. At the same time the average price of online purchases does not differ from average price of offline purchases. Nevertheless, differences in preferences do not allow to extend the conclusions made on online transactions on the whole set of sales.

Focusing on online purchases we collect information about purchased ticket. This includes name of performance, date and time of performance (season, year, month, day of week, hour), the tariff price of purchase, the price of purchase (after a personal discount), row and seat, seating area, date and time of purchase, time from purchase to play. Descriptive statistics of chosen tickets are presented in Table 3.

The analysis includes around 60 thousand transactions. The mean price of ticket bought is around 1000 rubles. The average attendance of seating area in a time of purchase is 44%. The majority of tickets is bought in advance. Two thirds of tickets are bought approximately 1-2 months before the performance, a fifth of transactions is made about 3 months before the play. Only 10 percent tickets are purchased in a week before the play.

Table 2. Comparison of offline and online purchases

Variable	All tickets (59919 obs.)	Offline Purchase (31539 obs.)	Online Purchase (28380 obs.)	Difference
Ballet	0.306	0.275	0.339	-0.064***
Top 10 rated opera	0.102	0.081	0.124	-0.043***
Top 100 rated opera	0.067	0.057	0.077	-0.019*
Top 10 rated ballet	0.570	0.595	0.544	0.051*
Balletmeister: Miroshnichenko	0.295	0.279	0.313	-0.035*
Choirmeister: Polonskiy	0.110	0.101	0.120	-0.019
Conductor: Abashev	0.223	0.219	0.227	-0.008
Conductor: Platonov	0.393	0.440	0.343	0.096***
Conductor: Currentzis	0.240	0.194	0.289	-0.095***
Golden Mask Laureat	0.206	0.181	0.233	-0.052***
Weekend	0.604	0.601	0.608	-0.007
High season	0.694	0.724	0.661	0.063***
Premiere of season	0.236	0.216	0.257	-0.040***
Price	1064.2	1045.7	1084.1	-38.3
Attendance	0.437	0.427	0.447	-0.021
Days to performance	36.1	39.5	32.5	-7.0***
Purchase in day of performance	0.088	0.076	0.101	-0.025**
Purchase in 1-7 days to performance	0.106	0.083	0.130	-0.046***
Purchase in 8-30 days to performance	0.277	0.266	0.290	-0.024***
Purchase in 31-60 days to performance	0.331	0.353	0.306	0.047***
Purchase in 61-120 days to performance	0.199	0.222	0.174	0.048***
Seating area 1	0.024	0.023	0.025	-0.002
Seating area 2	0.025	0.024	0.026	-0.002
Seating area 3	0.028	0.025	0.031	-0.006
Seating area 4	0.212	0.196	0.229	-0.033***
Seating area 5	0.105	0.107	0.104	0.003
Seating area 6	0.060	0.069	0.050	0.019***
Seating area 7	0.067	0.080	0.052	0.028***
Seating area 8	0.063	0.069	0.057	0.011***
Seating area 9	0.153	0.157	0.148	0.008
Seating area 10	0.109	0.121	0.095	0.025***
Seating area 11	0.155	0.130	0.182	-0.052***
		$\chi^2(32)$=55.4		p-value = 0.006

Notes: Stars in the difference column corresponds to p-value of t-test for the difference between offline and online purchase characteristic mean. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
χ^2 and its p-value indicates the difference between offline and online purchases in all reported characteristics.

Since we have extensive time period in data on online purchases, we may also reconstruct the history of purchases including all transaction information described above. The data include information on buyer ID, date of purchase, performances attended, number of tickets purchased and an average price of purchases. The Table 4 represents behavioral characteristics of online buyers. The average internet buyer has purchased tickets through the internet 2.4 times in the history of online shopping. The average number of tickets purchased through the internet is 5.2. On average the buyer purchases 2.3 tickets in an order. 83% of buyers demonstrate strong preferences for group of seats buying all tickets to the same group of seats.

Table 3. Descriptive statistics for chosen tickets

Variable	Obs	Mean	Std. Dev.	Min	Max
Price	59919	1064.2	946.9	100	8000
Attendance	59919	0.441	0.268	0	0.994
Days to performance	59919	36.1	27.8	0	128
Purchase in day of performance	59919	0.088	0.283	0	1
Purchase in 1-7 days to performance	59919	0.106	0.307	0	1
Purchase in 8-30 days to performance	59919	0.277	0.448	0	1
Purchase in 31-60 days to performance	59919	0.331	0.470	0	1
Purchase in 61-120 days to performance	59919	0.199	0.399	0	1
Online purchase	59919	0.481	0.499	0	1
Seating area 1	59919	0.024	0.152	0	1
Seating area 2	59919	0.025	0.156	0	1
Seating area 3	59919	0.028	0.165	0	1
Seating area 4	59919	0.212	0.408	0	1
Seating area 5	59919	0.105	0.306	0	1
Seating area 6	59919	0.060	0.236	0	1
Seating area 7	59919	0.069	0.249	0	1
Seating area 8	59919	0.063	0.243	0	1
Seating area 9	59919	0.153	0.359	0	1
Seating area 10	59919	0.109	0.311	0	1
Seating area 11	59919	0.155	0.362	0	1

Table 4. Behavioral characteristics of internet buyers

Variable	Obs	Mean	Median	Min	Max
Average time to purchase	7517	10.9	10	0	30
Number of tickets	7517	5.2	3	1	227
Number of orders	7517	2.4	1	1	83
Average number of tickets in order	7517	2.3	2	1	49
Average price of purchase	7517	1177.9	880	100	8160
	Obs	Mean	Share of 0	Share of 1	Share of rest
Share of 1-4 seating area	7517	0.36	0.57	0.31	0.12
Share of 5-7 seating area	7517	0.22	0.71	0.16	0.13
Share of 8-11 seating area	7517	0.42	0.53	0.36	0.11

4.2. SP data

The second source of data for the research is an online survey. The respondents who make the purchases through the Internet received an email requesting complete the survey. The online-survey conducted has two parts. The first one is dedicated to discrete choice experiment (DCE). This is a source of data about choice in hypothetical situations. Each hypothetical situation (choice set) is defined as a card with some hypothetical alternatives. Hypothetical alternative is characterized by a set of important attributes that was chosen following the results of qualitative study of theatregoers. Alternatives are described through type of performance, premiere play or not, adaptation, conductor, seating area and ticket price (Table 5). Consumer chooses one alternative per card. Relying on previous research where authors evidence that the optimal number of choice sets to be shown is between 6 and 13, we offer each respondent 6 to 10 sets to choose from (Caussade *et al*., 2005).

Table 5. Attributes and levels in discrete choice experiment

Attribute	Levels of attribute
Type of performance	Opera/ballet
Premiere play	Premiere/regular play
Adaptation	Modern/traditional
Conductor	Currentzis/Abashev/Platonov/Urupin
Seating area	From 1 to 11
Price	From 100 to 15000 rubles per ticket

The levels of attributes (Table 5) were chosen in a such way that the selected values correspond to real choice situations. The type of performance was selected to reflect those plays that usually presented in the Theatre: opera and ballet. Premiere reflects whether the play is one of premiere series or the performance has been showing for some time (regular play). Adaptation (modern or traditional) is responsible for interpretation of the work that is the basis of performance. Traditional adaptation reflects that director sought to stage the play as close as possible to the original work. Modern adaptation assumes non-standard approach to production. The conductors were chosen the highest fraction of plays conducted. Prices were also chosen based on real pricing strategy for seating areas in a current theatre season.

Once the attributes and levels of attributes were set, we produce an experimental design. The aim of experimental design is to determine the combination of attribute levels for each choice alternative.

Generating an experimental design, it is necessary to determine some key parameters of experiment. In our case the labelled design is chosen, the labels are determined by seating areas. Although the property of balanced design is desirable, it has not been considered as necessary (Kanninen, 2002). We sacrifice a balance of characteristics in favor of the experiment efficiency.

Using distribution of priors from estimation of RP models, we employ Bayesian D-efficient experimental design – fractional factorial design where the information from each choice situation is maximized.

Table 6 shows descriptive statistics by characteristics generated in experimental design. The mean price in experiment is higher than mean price in RP data, since RP data contain information for 6 seasons, but SP survey corresponds to the price for current season. Generally, it is seen that the experiment is practically balanced in terms of attributes levels.

Table 6. Comparison between chosen and unchosen alternatives' characteristics in SP data

Variable	All alternatives (22680 obs.)	Chosen alternatives (7560 obs.)	Unchosen alternatives (15120 obs.)	Difference
Price	2414.2	2043.1	2599.7	-556.6***
Ballet	0.50	0.56	0.47	0.09***
Premiere	0.49	0.52	0.48	0.05***
Modern	0.50	0.50	0.50	0.00
Conductor: Currentzis	0.25	0.37	0.19	0.18***
Conductor: Platonov	0.23	0.20	0.25	-0.05***
Conductor: Abashev	0.26	0.23	0.28	-0.05***
Conductor: Urupin	0.25	0.19	0.28	-0.09***
Seating area 1	0.09	0.06	0.11	-0.05***
Seating area 2	0.08	0.08	0.08	0.00
Seating area 3	0.09	0.09	0.09	0.00
Seating area 4	0.08	0.10	0.07	0.03***
Seating area 5	0.12	0.13	0.12	0.02*
Seating area 6	0.11	0.12	0.11	0.02*
Seating area 7	0.10	0.10	0.10	0.00
Seating area 8	0.10	0.12	0.09	0.03***
Seating area 9	0.10	0.10	0.10	0.00
Seating area 10	0.09	0.06	0.11	-0.05***
Seating area 11	0.04	0.03	0.05	-0.02*
			$\chi^2(19)$=38.1	p-value = 0.006

Notes: Stars in the difference column corresponds to p-value of t-test for the difference between characteristic of chosen and unchosen alternatives. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
χ^2 and its p-value indicates the difference between chosen and unchosen alternatives in all reported characteristics.

Table 6 allows to impose hypothesis about theatregoers' preferences on alternatives characteristics. Thus, chosen alternatives are cheaper than unchosen. Among performance characteristics respondents are likely to choose ballets rather than operas, premiere plays rather than regular ones, Currentzis among other conductors and middle seats among seating areas. These findings correspond to outcomes of preliminary RP data analysis that allow to expect the absence of bias in SP responses.

The second part of online survey includes questions about socio-demographic status and cultural participation of respondents. Table 7 describes the respondents in terms of their residence, gender, age, education graduated, income and other characteristics.

Table 7. Socio-demographic characteristics of online buyers

Variable	Obs	Mean	Std. Dev.	Min	Max
Place of residence: Perm	998	0.75	0.46	0	1
Place of residence: Perm region	998	0.07	0.26	0	1
Place of residence: other	998	0.17	0.38	0	1
Gender: Female	998	0.82	0.38	0	1
Age of respondent	998	40.2	12.2	18	73
Family status: Married or coupled	998	0.59	0.49	0	1
Education: some college	998	0.11	0.31	0	1
Education: higher	998	0.82	0.39	0	1
Education: PhD	998	0.08	0.27	0	1
Job: have subordinaries	998	0.43	0.50	0	1
Job: intellectual	998	0.91	0.29	0	1
Income: less than 14 thou. rub.	998	0.11	0.31	0	1
Income: between 15 and 29 thou. rub.	998	0.31	0.46	0	1
Income: between 30 and 49 thou. rub.	998	0.25	0.44	0	1
Income: between 50 and 69 thou. rub.	998	0.09	0.28	0	1
Income: between 70 and 99 thou. rub.	998	0.06	0.24	0	1
Income: more than thou. rub.	998	0.06	0.23	0	1
Income: no answer	998	0.12	0.33	0	1
Visits per year: less than 1	998	0.19	0.39	0	1
Visits per year: 1-4	998	0.53	0.50	0	1
Visits per year: more than 4	998	0.29	0.45	0	1
Time to purchase: in a week to play	998	0.34	0.47	0	1
Time to purchase: in a month to play	998	0.21	0.41	0	1
Time to purchase: in a two months to play	998	0.34	0.47	0	1
Time to purchase: no answer	998	0.11	0.31	0	1
Sophistication: low	998	0.11	0.31	0	1
Sophistication: middle	998	0.31	0.46	0	1
Sophistication: high	998	0.62	0.48	0	1
Visit other theaters	998	0.70	0.46	0	1
Goal of visit: enjoy a show	998	0.95	0.21	0	1
Goal of visit: educational	998	0.22	0.42	0	1
Goal of visit: go out	998	0.13	0.33	0	1
Goal of visit: have fun	998	0.16	0.36	0	1

The majority of respondents is Perm residents while significant part of respondents (17%) lives outside Perm region. This fact is also proved by phenomenon of “cultural tourism”, when travelling people visit cultural events. Four fifths of respondents are female that is exactly correspond to real gender proportion of theatre’ visitors according to internal theatre survey. The average respondent is 40 years old, married or coupled, have higher education and intellectual type or work. The majority of respondents have monthly income between 15 and 29 thousand rubles (according to portal of Perm statistics the official wage in Perm in 2016 is 28 thousand rubles).

5. Empirical Results

The framework of empirical results is arranged in accordance with data description. The first part of section is dedicated to discussion of estimation results based on RP data. The second part consists of SP data results. At the end of the section we discuss results on combined RP/SP dataset.

5.1. RP results

First of all, we should test, whether the results based on online sales may be generalized to a whole set of purchases. Therefore, we estimate multinomial logit model on data of offline and online purchases (Table 8). Since the correct estimation of price sensitivity is crucial for the development of pricing strategy, and the results of estimation demonstrate that offline and online buyers differ in price elasticity, we are forced to confine ourselves to conclusions concerning online purchases only. However, online buyers are much more elastic than those who purchase offline that leads to the necessity to adjust pricing strategy in a greater degree in relation to online sales.

Table 9 represents detailed regression results on multinomial logit model and shows that, after adjusting for a variety of characteristics and seating area dummies individuals express significantly lower price elasticity estimates. In each regression, the dependent variable is a latent utility from choice a ticket from a certain seating area at a performance.

Table 8. Comparison of multinomial logit results between offline and online purchases

	(1)	(2)	(3)
	All tickets	Offline purchases	Online purchases
Ln (Price)	-0.272***	-0.145**	-0.432***
	(0.035)	(0.051)	(0.050)
Number of obs.	634349	333637	300712
Number of choice sets	59919	31539	28380
Number of parameters	192	182	182
Log. Likelihood	-125932.5	-66813.0	-58563.6
BIC	254430.2	135940.6	119422.9

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All estimated models contain controls for attendance, seating area dummies, performance characteristics and purchase characteristics.

The key finding in column 4 of Table 9 is that online purchasers has price sensitivity at the level of - 0.42. This value cannot be directly interpreted as price elasticity but it takes the role of price sensitivity in the model and may be employed in model comparing. Thus, the changes in price sensitivity across columns in Table 9 point to the need to account for seats quality, performance and consumer characteristics.

Table 9. Logit results for online purchases

	(1)	(2)	(3)	(4)
Ln (Price)	-0.712***	-0.544***	-0.432***	-0.416***
	(0.034)	(0.050)	(0.050)	(0.067)
Controls:				
Attendance	+	+	+	+
Seating area dummies	+	+	+	+
Performance characteristics	-	+	+	+
Purchase characteristics	-	-	+	+
Behavioral characteristics	-	-	-	+
Number of obs.	300712	300712	300712	300712
Number of choice sets	28380	28380	28380	28380
Number of parameters	12	142	182	272
Log. Likelihood	-59686.7	-59206.4	-58563.6	-35351.7
BIC	119524.9	120204.0	119422.9	74134.3

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As discussed earlier, multinomial logit model does not allow to account for consumers' heterogeneity. For this purpose, we use latent class model. Table 10 demonstrates how price sensitivity estimates changes with splitting into different number of classes. When we estimate the model on the whole sample, the price parameter is – 0.6. As the number of classes increases, price elasticity estimates for classes change in different directions.

A separate consideration is required for determination of the number of classes in latent class model. For this purpose, the model has been tested using cross-validation technique on different number of classes. Cross-validation has demonstrated that the maximum of log likelihood is achieved for the model with four classes.

Column 4 of Table 10 presents results for optimal splitting population on different classes. It is seen that consumers from the first class are less price sensitive, the most price sensitive individuals are in third class, the rest two classes are located between them. Table 10 demonstrates the differences in reactions to price change, but does not allow to explain these differences. Table 11 with estimates of class membership parameters allows to describe the classes obtained in Table 10.

According to Table 11 the most sensitive to price change segment (class 3) expectedly acquires cheaper tickets in average. They have shorter history of online purchases probably because of either rare visits in the theatre or rare purchases through the internet. The data show third segment buys lower number of tickets in an order that most likely means going to the theatre alone. They also rarely visit popular plays: premieres, ballets, plays conducted by Currentzis. Choosing the tickets, they prefer seats in the middle and at the end of house. Thus, the strong price sensitivity of this segment also matches with the preferences for performances and seats in a house.

The least sensitive to price change segment (class 1) expectedly buys more expensive tickets and also has shorter history of online purchases. Among performances they more often attend ballets and those that conducted by Currentzis. Among the seats they regularly prefer the first rows in the house of the theatre (1 – 4 seating areas). The preferences of this segment also seem to be consistent with their pricing behavior.

Among two remaining segments there is at least one interesting group of visitors (class 4). They demonstrate frequent attendance of the theatre. Buying a ticket they prefer less attended seating areas that are located at the end of house. Expectedly they purchase tickets at a lower price, also acquire lower number of tickets in order and attend the least popular performances (regular plays, operas).

The results based on RP data allow to identify and describe consumer segments in relation to preferences for performance and seat along with a sensitivity to a price change. The main drawback of RP results is that multinomial logit and latent class logit model a choice of seating area conditional on the choice of performance.

Table 10. Latent class logit results for online purchases

	Number of classes			
	1	2	3	4
Weighted average parameter:				
Ln (Price)	-0.602^{***}	-0.777^{***}	-0.818^{***}	-1.051^{***}
	(0.041)	(0.039)	(0.051)	(0.067)
Attendance	-0.863^{***}	-1.063^{***}	-0.995^{***}	-1.031^{***}
	(0.044)	(0.045)	(0.072)	(0.080)
Class 1:				
Ln (Price)	-	-0.431^{***}	-0.409^{***}	-0.481^{***}
		(0.038)	(0.050)	(0.041)
Attendance	-	-0.782^{***}	-0.771^{***}	-0.880^{***}
		(0.041)	(0.061)	(0.075)
Class share		0.439	0.403	0.291
Class 2:				
Ln (Price)	-	-1.048^{***}	-1.122^{***}	-1.025^{***}
		(0.041)	(0.052)	(0.068)
Attendance	-	-1.283^{***}	-0.900^{***}	-0.654^{***}
		(0.048)	(0.077)	(0.069)
Class share		0.561	0.259	0.186
Class 3:				
Ln (Price)	-	-	-1.075^{***}	-1.890^{***}
			(0.051)	(0.085)
Attendance	-	-	-1.336^{***}	-1.236^{***}
			(0.079)	(0.088)
Class share			0.338	0.188
Class 4:				
Ln (Price)	-	-	-	-1.094^{***}
				(0.066)
Attendance	-	-	-	-1.282^{***}
				(0.087)
Class share				0.334
Number of obs.	300712	300712	300712	300712
Number of choice sets	28380	28380	28380	28380
Number of parameters for each class	52	52	52	52
Log. Likelihood	-59543.1	-45899.1	-40060.5	-38075.2
BIC	119742.1	92851.3	81763.2	78381.5

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This does not allow to identify a probability of null alternative choice, which reflects either a choice of other performance or a choice of not to go to a theatre. Moreover, we cannot perform a proper analysis of cross-price elasticity of demand for seating areas on RP data, since we may only predict a change in a share of bought tickets across seating areas but not a change in a mass of tickets in general. Finally, RP behavioral data give insufficient description about segments that do not allow to compare the results with already existed in literature and to develop marketing strategies. These factors emphasize the use of stated preferences data.

Table 11. Results for class membership model with 4 latent classes

Variable	Class			
	1	2	3	4
Purchase in 1-7 days to performance		-1.491***	1.785***	-1.859***
Purchase in 8-30 days to performance		3.170***	2.212***	3.581***
Purchase in 31-60 days to performance		1.802***	2.504***	1.886***
Purchase in 61-120 days to performance		-2.302***	3.898***	2.792***
Log of average price of purchase		-0.681***	-0.964***	-1.231***
Log of tickets purchased		0.486***	-0.808***	0.873***
Log of average number of tickets in order		0.358***	-0.475***	-0.534***
Share of purchases in 1-7 days to performance		-0.831***	3.574***	2.977***
Share of purchases in 8-30 days to performance		2.868***	5.465***	4.838***
Share of premiere plays		0.173***	-0.409***	-0.685***
Share of plays with Currentzis		-0.212***	-0.575***	-0.404***
Share of ballets		-0.276***	-0.517***	-0.591***
Share of tickets in 5-7 seating areas		2.216***	1.087***	1.683***
Share of tickets in 8-11 seating areas		1.165***	1.663***	2.463***
Constant		-1.231***	-0.981***	-1.527***
Parameters in latent class model:				
Ln (Price)	-0.481	-1.025	-1.890	-1.094
Attendance	-0.880	-0.654	-1.236	-1.282
Class share	0.291	0.186	0.188	0.334

5.2. SP results

The estimation results of multinomial logit models on SP data represented in Table 12. The SP model includes only type of show (opera/ballet), indicator of whether the production is premiere, adaptation (modern/traditional), conductor (Currentzis, Abashev, Platonov, Urupin), price area (from 1 to 11) and price. Alternative specific constants represent different price areas as in RP data. In each regression, the dependent variable is a latent utility from choice of a ticket from a proposed set of three tickets. Table 12 shows regression results adjusting for performance characteristics listed above and alternative specific constants. The decrease in price sensitivity estimate testifies the need to account for these variables. As in the case of RP part, we generalize multinomial logit model by a latent class model to account for consumers heterogeneity. The differences in price parameters between classes are demonstrated in Table 13. The key findings of Table 13 in columns 1 and 3 are that price sensitivity weighted by classes is – 0.32, whereas the price sensitivity varies between classes from - 0.69 to - 0.28.

Table 12. Results for multinomial logit models on SP data with different set of controls

	(1)	(2)	(3)
Ln (Price)	-0.235***	-0.320***	-0.334***
	(0.011)	(0.013)	(0.013)
Controls:			
Seating area dummies	-	+	+
Performance characteristics	-	-	+
Number of obs.	22680	22680	22680
Number of choice sets	7560	7560	7560
Number of parameters	1	11	17
Log. Likelihood	-13973.0	-13737.7	-13277.6
BIC	27956.0	27585.7	26725.8

Standard errors in parentheses. Significance levels are: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13. Latent class logit results on stated preferences data

	Class		
	1	2	3
Weighted average parameter:			
Ln (Price)	-0.323***	-0.355***	-0.386***
	(0.013)	(0.019)	(0.024)
Class 1:			
Ln (Price)	-	-0.155***	-0.412***
		(0.013)	(0.035)
Class share		0.643	0.169
Class 2:			
Ln (Price)	-	-0.550***	-0.687***
		(0.030)	(0.022)
Class share		0.357	0.160
Class 3:			
Ln (Price)	-	-	-0.277***
			(0.022)
Class share			0.671
Number of obs.	22680	22680	22680
Number of choice sets	7560	7560	7560
Number of parameters for each class	17	17	17
Log. Likelihood	-13277.6	-12559.8	-12440.1
BIC	26725.8	25811.6	26093.7

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Description of latent classes can be found in Table 14, where the estimation results represents comparison with the class 1 (column 1). According to class membership parameters the most sensitive to price change segment (column 2 in Table 14) includes visitors living in Perm. The representatives of this segment are older than consumers from the first segment, more often married, have higher education and possess lower income compared to other segments. Considering that four fifths of theatre audience are women, the majority of male audience falls into this segment. Moreover, they demonstrate higher frequency of attendance (more than 4 times a year). This class contributes 16% of the theatre consumers.

Respondents that belong to class 1 (column 1) are younger and more often unmarried, have no subordinates at work and are predominantly engaged in manual labor. They actively visit the theatre during a year (1 - 4 times a year) and do not visit other theatre in Perm. As for the rest the segment is quite heterogeneous, since there are no distinctions on other socio-demographic characteristics. The first class accounts for 16.9% of the theatre customers.

Table 14. Results for latent class membership model on stated preferences data

Variable	Class1	Class2	Class3
Place of residence: Perm region		0.508***	-0.015
Place of residence: other		-0.177***	0.588***
Gender: Female		-0.058***	0.046***
Age of respondent		-0.139***	-0.133***
Age of respondent sq.		0.056*	0.052*
Family status: Married or coupled		0.480***	0.043*
Education: some college		-0.875***	0.406***
Education: PhD		-0.388***	-0.474***
Job: have subordinaries		0.257***	0.624***
Job: intellectual		0.111***	0.324***
Category of income		-0.718***	0.084***
Income: no answer		-0.072***	-0.551***
Visits per year: 1-4		-0.921***	-0.119***
Visits per year: more than 4		0.749***	-0.491***
Time to purchase: in a month to play		0.997***	0.339***
Time to purchase: in two months to play		0.415***	-0.447***
Time to purchase: no answer		0.732***	0.108***
Sophistication: high		-0.052***	0.849***
Visit other theaters		0.703***	0.563***
Goal of visit: educational		-0.126***	-0.072**
Goal of visit: go out		0.357***	0.159***
Goal of visit: have fun		0.322***	-0.106***
Constant		0.029***	0.332***
Characteristics of class:			
Ln (Price)	-0.412***	-0.687***	-0.277***
Class share	0.169	0.160	0.671

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Class 3 (column 3) members are much less sensitive to price, compared to those in Classes 1 and 2, and by implication willing to pay a much higher price for theatre tickets. It mostly includes married women with higher income. Representatives of third segment are mostly engaged in intellectual labor and have subordinates at work. This segment is heterogeneous enough and includes people, which in real situations show different patterns of behavior, but possess the same reaction to price change. From the one hand, it includes visitors living outside Perm region. This explain low frequency of attendance. They expectedly rarely visit Perm Opera and Ballet Theatre and buy the tickets a month before a play. From the other hand, the segment includes highly sophisticated visitors which remember the last visit to the theatre and plan the next in advance. As a main goal of visit they notice the aim of going out. The heterogeneity of this class is partly explained by the fact that this class is the most numerous and includes different consumers. The share of the class is a 67.1% of the theatre customers. Thus, the latent class model divided the theatre market into three segments. The result of audience segmentation largely coincides with the previous ones (Grisolia & Willis, 2012). Partly due to different data available and the specificity of theatre audience segment description has some peculiarities compared to preceding papers, that will be discussed in details later.

5.3. RP and SP results

Table 15 represents detailed regression results on multinomial logit model on RP, SP and combined RP-SP datasets. In each regression, the dependent variable is the utility gained from chosen seating area at a performance. All regressions in the table include log of price, attendance of a seating area and other control variables. Discrete choice experiment does not include the attendance of a seating area at the time of purchase, this parameter is not estimated in SP part (column 2 in Table 15). The differences in a number of observations in regressions is explained by different data generating processes. Finally, the log likelihood of the three models is not directly comparable because of differences in sample size and number of estimated parameters.

Generally, the models can be compared in terms of standard errors values. Since the efficient experimental design allows to induce more variability in attributes in the SP model, it results in the fact that SP results demonstrate smaller standard errors compared to RP results. This supports the efficiency of SP DCE design.

In column 3 of Table 15 regression results of the model on joint RP-SP data is reported. It is seen that estimates obtained on joint RP-SP data are in interval between RP and SP parameters that is consistent with the estimation procedure. At the same time, RP-SP estimates have smaller standard errors compared to both RP and SP results and, consequently, more variables have a statistically significant impact on choice, including price. Moreover, RP-SP model is also preferred over SP and RP, since by construction it includes actual choice made by individuals and by virtue of efficient experimental design provides more efficient estimates of parameters.

Table 15. Comparison of multinomial logit results for RP, SP and joint RP and SP data

	(1) RP data	(2) SP data	(3) Joint RP and SP data
Ln (Price)	-0.602***	-0.333***	-0.422***
	(0.041)	(0.013)	(0.012)
Attendance	-0.863***	-	-0.726***
	(0.044)		(0.040)
Seating area 2	0.187	0.355***	0.305***
	(0.130)	(0.073)	(0.063)
Seating area 3	0.293*	0.363***	0.352***
	(0.125)	(0.072)	(0.062)
Seating area 4	2.067***	0.532***	1.322***
	(0.102)	(0.073)	(0.055)
Seating area 5	1.383***	0.383***	0.894***
	(0.109)	(0.068)	(0.058)
Seating area 6	0.622***	0.248***	0.540***
	(0.118)	(0.069)	(0.061)
Seating area 7	0.737***	0.045	0.478***
	(0.119)	(0.071)	(0.063)
Seating area 8	0.673***	0.323***	0.656***
	(0.121)	(0.071)	(0.063)
Seating area 9	1.135***	0.025	0.726***
	(0.117)	(0.075)	(0.060)
Seating area 10	0.301*	-0.517***	0.033
	(0.127)	(0.080)	(0.063)
Seating area 11	0.196	-0.761***	0.081
	(0.153)	(0.097)	(0.069)
Number of obs.	300712	22680	323392
Number of choice sets	28380	7560	35940
Number of parameters	52	17	58
Log. Likelihood	-59543.1	-13277.6	-71328.6
BIC	119524.1	26725.8	143393.0

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Seating area 1 is a base category.

Table 16 presents results for latent class model with various number of classes calibrated on joint RP-SP data. Since as the number of classes increases, Log Likelihood rises, we cannot choose the number of classes based on its value. The number of classes selected can be selected using the Bayesian Information Criterion (BIC), that demonstrates, whether it is worth to increase the complexity of the model by adding additional latent classes. According to Table 16 we may conclude that the model with four classes performs better in terms of Log Likelihood and BIC criteria. Model with five classes fails to converge to global maximum that points at impossibility to divide the sample on higher of statistically different classes. Therefore, we interpret and analyze classes according to the model with four classes.

In Table 16 We also can follow the change in price sensitivity estimates as the number of classes increases. The estimate of price sensitivity weighted by the size of classes is – 0.42, whereas the price sensitivity for classes varies from - 0.63 to - 0.32. The description of the classes that explain the differences in price sensitivity is represented in Table 17.

Table 16. Latent class logit results for joint RP and SP data

	Number of classes			
	1	2	3	4
Weighted average parameter:				
Ln (Price)	-0.422***	-0.396***	-0.392***	-0.423***
	(0.012)	(0.012)	(0.013)	(0.019)
Attendance	-0.726***	-0.863***	-0.772***	-0.875***
	(0.040)	(0.043)	(0.050)	(0.102)
Class 1:				
Ln (Price)	-	-0.362***	-0.318***	-0.625***
		(0.012)	(0.011)	(0.027)
Attendance	-	-0.937***	-0.309***	-0.624***
		(0.040)	(0.032)	(0.091)
Class share		0.567	0.310	0.195
Class 2:				
Ln (Price)	-	-0.465***	-0.551***	-0.355***
		(0.013)	(0.021)	(0.015)
Attendance	-	-0.810***	-1.122***	-0.585***
		(0.049)	(0.069)	(0.101)
Class share		0.433	0.291	0.288
Class 3:				
Ln (Price)	-	-	-0.351***	-0.425***
			(0.014)	(0.022)
Attendance	-	-	-0.887***	-1.102***
			(0.053)	(0.099)
Class share			0.399	0.314
Class 4:				
Ln (Price)	-	-	-	-0.320***
				(0.013)
Attendance	-	-	-	-1.177***
				(0.111)
Class share				0.203
Number of obs.	323392	323392	323392	323392
Number of choice sets	35940	35940	35940	35940
Number of parameters for each class	58	58	58	58
Log. Likelihood	-71328.6	-66234.1	-62701.4	-59665.6
BIC	143393.0	133939.8	127610.2	122274.5

Standard errors in parentheses. Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The model of class membership describes the differences in classes with respect to class 1. The results reveal that all variables included in the class membership model are significant, thus, the classes statistically differ from each other by these characteristics.

For socio-economic characteristics of theatregoers from the most sensitive to price change segment (column 1) purchase the cheapest tickets in average. However, they stand out by longer history of purchases and more often acquire one or two tickets per order. Hence, they demonstrate frequent theatre attendance and prefer to visit the theatre alone. Class 1 is characterized by higher attendance of ballets. Among conductors they do not demonstrate preferences to any of them. They usually prefer to purchase tickets in back seating areas (from 8 to 11), which are sold at a lower price. At the same time, the most sensitive segment shows the least sensitivity to attendance of the seating area. Purchasing the ticket, they have to choose between an affordable price and convenient location of the seat. Since the most attractive seats in terms of price and location are purchased with a higher speed, representatives of class 1 sacrifice convenience in favor of affordable price. From the point of socio-demographic characteristics class 1 includes people who lives in Perm region, unmarried or is not in a relationship and has higher education. The most sensitive respondents possess lower income. This class also consists of mature people in contrast with those in classes 2 and 3. We also may call them as “higher sophisticated” spectators, since they are well informed in the repertoire of the theatre. At the same time, consumers from class 1 more often visit performances of other Perm theatres, which in some sense is an indicator of omnivorous range of tastes. This class is thin and accounts for 19.5% of spectators.

Class 4 includes representatives of the least sensitive segment (column 4 in Table 17). They expectedly purchase more expensive tickets in average in contrast to other three classes and possess the highest income among other respondents. Among performances they prefer operas rather than ballets. They equally visit premiere and regular play. The respondents of class 4 belong to admirers of plays conducted by Currentzis. This allows to say that representatives of this segment consume tickets with higher quality of seat and performance. Besides, they demonstrate the highest sensitivity to the attendance of seating area. Continuing the previous discussion on the balance between an affordable price and a convenient seat, we may conclude that representatives of class 4 are ready to pay higher price for a convenient location in the house. Moreover, low sensitivity to a price change and willingness-to-pay more for good seats may be associated with low frequency of visits. They also differ from other segments by age, visitors of fourth segment are older than others people. Moreover, this class is characterized by the relatively high theatre attendance (1 - 4 times a year). The share of this class constitutes 20.3% of theatre audience.

Table 17. Results for class membership model on joint RP and SP data

Variable	Class 1	2	3	4
Log of average price of purchase		0.222***	0.186***	0.396***
Log of tickets purchased		-0.435***	0.207***	-0.306***
Log of average number of tickets in order		0.527***	-0.356***	0.208***
Share of premiere plays		0.427***	-0.848***	-0.303***
Share of plays with Currentzis		0.427***	0.281***	0.476***
Share of ballets		-0.903***	-0.543***	-0.580***
Share of tickets in 5-7 seating areas		-0.284***	0.792***	0.149***
Share of tickets in 8-11 seating areas		-0.891***	-0.262***	-0.565***
Place of residence: Perm region		-0.200***	-0.390***	-0.603***
Place of residence: other		0.103***	-0.008	0.012
Gender: Female		0.518***	-1.468***	-0.621***
Age of respondent		-0.043***	0.103***	-0.046***
Age of respondent sq.		0.018*	-0.049*	0.019*
Family status: Married or coupled		0.456***	1.526***	0.679***
Education: some college		0.303***	0.675***	1.139***
Education: PhD		-0.601***	-0.115***	-0.108***
Job: have subordinaries		0.127***	-0.395***	0.557***
Job: intellectual		-0.506***	0.838***	0.751***
Category of income		0.107***	-0.185***	0.146***
Income: no answer		0.295***	1.162***	0.393***
Visits per year: 1-4		0.161***	1.448***	0.007
Visits per year: more than 4		0.835***	0.534***	-0.228***
Time to purchase: in a month to play		0.419***	0.309***	0.675***
Time to purchase: in two months to play		0.566***	0.702***	-0.036***
Time to purchase: no answer		0.527***	-0.487***	-0.702***
Sophistication: high		-0.226***	0.486***	-0.127***
Visit other theaters		0.146***	-0.292***	-0.207***
Goal of visit: educational		-0.414***	0.197***	0.261***
Goal of visit: go out		-0.355***	-1.026***	0.253***
Goal of visit: have fun		0.303***	-0.310***	0.642***
Constant		0.736***	0.370***	0.482***
Parameters in latent class model:				
Ln (Price)	-0.625***	-0.355***	-0.425***	-0.320***
Attendance	-0.624***	-0.585***	-1.102***	-1.177***
Class share	0.195	0.288	0.314	0.203

Class 3 is similar to class 1 (the most elastic by price) to some degree (column 3 in Table 17). They are also higher elastic by price change and possess the lowest income among other segments. Representatives of class 3 possess the longest history of tickets purchased through the internet and prefer to visit the theatre alone or in pairs (have smaller average number of tickets in an order). From other segments, they differ by more rare visits of premiere plays that is linked with more expensive tickets on premiere plays. Since the majority of consumers in the class are residents of Perm, they may visit premiere plays afterwards, when a performance moves from a premiere to a regular category. Besides, representatives of class 3 are more often married, have an intellectual job with no subordinates. They belong to the category of active spectators (visit the theatre 1 - 4 times a year). Among other segments they stand out for higher sophistication and loyalty. They mention educational as a main goal of a visit. This class is prevailing and accounts for 31.4% of theatre audience.

Class 2 is similar in many respects to class 4 (column 2 in Table 17). They are also less sensitive to price change and more sensitive to seat location. They differ from the rest by the highest mean price of ticket purchased. In comparison with other segments they acquire more tickets in an order, thus, they tend to attend the theatre with accompanying persons. Besides, the representatives of the consumer group usually purchase tickets in advance that distinguishes them from the rest. Class 2 is characterized by the attendance of popular productions: premieres and plays conducted by Currentzis. Among the seats in the house they prefer the first seating areas (from 1 to 4). High income and preferences for the most popular performances and the most expensive seats allow to consider the class as a representative of affluent attendees.Similar to the results of latent class model on SP part of data class 2 also includes people which demonstrate the same reaction for price change, but differ in their socio-demographic and behavioral description. The class includes some small consumer groups, who differ by their description from the rest of the class, and whose characteristics cannot be attributed to the whole segment, but still require separate consideration, since their characteristics prescribe the use of distinctive marketing tools of influence.

Thus, people from other regions constitute only 17% of the sample, and their group size does not allow to separate them as a segment. Nevertheless, the analysis reveals that they are not statistically differ from customers from class 2 in terms of price sensitivity. Descriptive statistics show that 90% of respondents have higher education and only 10% have some secondary or secondary professional education. Class 2 also includes those 10% of people without higher education. In the survey, only 9% of respondents describe their job as physical rather than intellectual. This small group of people is also included in class 2.

Mixed structure of class 2 is reflected in some socio-demographic and behavioral characteristics. Thus, the class is characterized by shorter history of online purchases. At the same time, among all segments people who visit the theatre more than four times a year are more presented in the class 2. This contradiction may indicate that online purchases constitute only a part of the whole history of visits. However, such conclusions may be the result of mixed structure of class. Moreover, people who attend the theatre from 1 to 4 times a year are also more presented in this class. Hence, we may conclude that active visitors (who attend the theatre 1-4 times a year) and theatregoers (who visits more than 4 times a year) are not statistically different in terms of price sensitivity. Class 2 is also characterized by lower level of sophistication that may be associated with the significant share of people from other regions. At the same time, class 2 demonstrates the highest attendance of other Perm theatres. This class is enough numerous and contributes 28.8% of the theatre market.

6. Practical implication

Finally, segmenting of theatre audience and identification of their preferences allow to develop practical recommendations for increasing the effectiveness of pricing using price discrimination methods. In the theory, the methods of price discriminations, setting a different price schedule to each individual, allow a firm to extract more profits by appropriating a part of consumer surplus. Until quite recently, first-degree price discrimination has been extremely rare in practice, since it requires information on consumer's reservation prices. Nowadays available large datasets on individual behavior allow to reveal or estimate consumer values of willingness-to-pay.

The term "first-degree price discrimination" is rather a theoretical concept than a specific price strategy. In practice the sellers use strategies of personalized, tailored or conditioning pricing. These practices imply approximately the same idea, but are slightly different from each other by the framework of application. In this research, we follow the logic of Acquisti and Varian (2004), using term "price conditioning". While first-degree price discrimination refers to charging each consumer their full reservation value, price conditioning as imperfect form of first-degree price discrimination assumes charging consumers different prices, not necessarily their full reservation values.

The case of theatre provides an auspicious context for price conditioning. First, a significant part of current purchases (about 50%) occurs online, that allows to identify a consumer and condition pricing strategy based on his purchasing history. Second, the theatre has already used price discrimination strategy based on explicit consumer characteristics (second-degree price discrimination). Third, available individual-level data on purchases of a particular performance allow to study the theatre audience empirically and develop individual pricing strategies. Thus, real data on tickets purchases and survey data on hypothetical choice as well as socio-demographic characteristics allow to propose specific instruments for tailored pricing.

Class 1: Low-brow customers. This is a consumer of popular culture, who enjoys ballets rather than operas, visits intelligible traditional plays, also attends plays of other theatres in Perm. These people are the most sensitive to price change, buy the cheapest tickets in average compared to other classes. Choosing a ticket, they mostly pay attention to price rather than quality of performance or seat. Expectedly they choose seats in circle or upper circle, which seems to be rational for a person with a low income. They also demonstrate high frequency attendance. Among less pronounced attributes this class includes people living in Perm region (these people constitute only 17 percent from the whole set of respondents), unmarried people (41 percent) and those, who possess the lowest category of income (less than 14 thousand rubles). Taking into account price sensitivity and lack of scrupulousness we may propose the theatre management to discount the prices on performances and seats in the cases when they do not fill out. Whereas, low-brow customers mostly rely on prices, they will respond to personal discounts. Besides, high frequency attendance allows to propose discounts depending on the number of tickets purchased or the system of subscriptions.

Class 2: Affluent customers. This is a wealthy type of theatregoer, who prefer premiere plays and performances conducted by Currentzis. In the house the stalls is the most preferred seats for them. It stands to mention that this class is the only that purchase the seats in the stalls. Members of this group demonstrate price insensitivity, consequently, they purchase the most expensive tickets in average compared to other consumers. This class expectedly include people with high income. Thus, we may conclude that purchasing a ticket these people make judgements about performance and seat quality by ticket price. Hence, we may offer the theatre management to maintain a high level of ticket prices on the seats in the stalls. It is also in the interest of theatre to make the full-fare ticket more valuable to visitors with higher willingness-to-pay and to make discounts less valuable. Theatre may offer different upgrades or enhanced service to higher willingness-to-pay visitors, for example, additional paid services, such as priority access to cloakroom or parking lot.

Class 3: Old theatre friends. This is a loyal Perm resident, who does not visit other theatres in Perm, actively visits Perm Opera and Ballet Theatre and demonstrates a long purchasing history. In addition, they demonstrate higher sophistication compared to other classes, that is they remember their past consumption and plan future visit to the theatre in advance. Members of this class have equal preferences according to operas and ballets and different conductors. However, they prefer to visit regular plays, probably they are willing to wait for lower price, when the play will move from the category of premiere to the category of regular. Besides, considering their price sensitivity and low income visits to regular plays allow them to save money in favor of frequent theatre visits. Among seats in a house they prefer seats in the middle (tiered stalls and circle), that are considered as the best in terms of relative quality to price. Moreover, old theatre friends tend to purchase tickets at the start of sales. Thus, the theatre may employ the strategy of dynamic pricing: make discount on seats in the middle of the house at the start of sales and increase the prices on these seats as the house fills up. Besides, with the purpose of keeping customers of this class the theatre may propose them free access to different additional events related to the life of the theatre (lectures about performances, meetings with artists and conductors) to maintain their high involvement.

Class 4: High-brow customers. This intellectual type of theatregoer appreciates the quality of performances and seats. They enjoy expensive plays but visit not the most expensive seats in a house (seats in the middle of the house). Members of this group prefer operas, that is considered as more complicated for understanding product rather than ballet, and performances conducted by Currentzis. As for socio-demographic status of this class, they have higher income, engaged in intellectual labor and have job subordinates. Thereby, realizing that demand for seats in tiered stalls and circle is made mainly by people from classes 3 and 4, and we may propose to make discounts at the start of sales (2-3 months before a play) for old theatre friends and increase the prices a month before a play for high-brow customers. Besides, high-brow customers may be interested in some exclusive theatre events, that they may attend for a fee.

7. Conclusion

Analysis of empirical studies devoted to performing arts market revealed that the problem of finding an effective pricing strategy is of great interest among researchers. In Russia, this point arises from the current financial state of theatres. According to open data portal of the Ministry of Culture[4], in 2016 Perm theatre covered only 17 percent of total expenses by income from ticket sales, the major part came from regional budget (75%) and the rest 8 percent was sponsorship.

In performing arts market the issue of effective pricing strategy is complicated by the specific characteristics of a product. Modelling the demand one should account for combined structure of a product. Purchasing a ticket, a consumer demands for a performance with a set of specific attributes, as well as for a seat in a house. Moreover, theatrical production is an experience good, that is consumer’s choice of performance in many respects depends on past consumption. In studies devoted to the discussion of pricing strategies theatrical productions are considered to be perishable goods. This category describes products that cannot be inventoried

[4] https://opendata.mkrf.ru

and sold after a time of play. Besides, the theatre audience is substantially heterogeneous in terms of visit purpose, ability to perceive quality, willingness to pay.

It is proved that price discrimination is an effective way to charge prices for perishable goods (Hetrakul & Cirillo, 2014). Considering heterogeneous theatre audience, the strategy of price discrimination should be developed in the context of various consumer segments. Thus, the aim of this paper is to develop marketing tools of influence for different theatre segments, that will allow to increase theatre revenue from ticket selling.

Development of price discrimination strategy requires data on consumer's purchase history, his behavioral as well as his socio-demographic characteristics. In the study, we employ data on internet ticket purchases that allows to observe consumer's name, email and the history of her attendance. Additionally, we collect experimental data on consumer's choice in some hypothetical situations. Experimental data permits to induce necessary variation in attributes that is insufficiently observed in real data. Questions on consumer's cultural participation and socio-demographic status allow to collect and, afterwards, describe consumer groups. Thus, joint dataset with real and survey data combines benefits and eliminates weak spots of each approach.

In order to identify consumer segments among theatre audience we employ a particular class of discrete choice models (DCM) – latent class model. LCM is a powerful tool, since gives insights into consumer segments and provides guidance to shape marketing policy. In effect, the model provides a clear picture of existing theatre audience and marketing strategies that should be applied to different types of theatregoers. The LCM model divides visitors on low-brow customers, affluent attendees, old theatre friends and high-brow customers. Taking account of price sensitivity of low-brow customers and lack of scrupulousness we may propose the theatre management to discount the prices on performances and seats in the cases when they do not fill out. Realizing that this segment mostly relies on prices at the time of buying, discounts on poorly filled performances and seats in the house will attract them to purchase the ticket. Since affluent attendees is the only segment that purchases the seats in the stalls, we may propose the theatre to maintain a high level of prices on the seats in the stalls. Besides, the average check of these consumers may be increased by offering additional paid services. Since, old theatre friends are sensitive to price change and tend to purchase tickets at the start of sales, it is rational to employ the strategy of dynamic pricing: make discounts on seats in the middle of the house at the start of sales and increase the prices on the seats as the house fills up. The segment of high-brow customers differs by consumption of quantitative productions and is indifferent to price change. To increase income from this segment the theatre may propose them paid exclusive theatre events.

Summarizing the research, we should emphasize some restrictions that limit the inference based on results. The most important restriction is that we may infer the results only for those theatregoers who purchase tickets online through the theatre website. Although focus on online purchases does not allow to discuss marketing instruments with respect to theatregoers purchasing tickets in a ticket office of the theatre. It does not debase our marketing recommendations, since initial comparison of offline and online purchases reveals that offline buyers are less elastic by price. This results in appropriateness of pricing strategy based on online purchases only because offline buyers have higher willingness-to-pay for a ticket. Moreover, one should differentiate the price between ticket office and website, but this needs a special analysis. A main drawback of used methodology of latent class model for a market segmentation is that it cannot identify small consumer segments, because it provides little statistical difference from the obtained ones. There may be some small groups of theatregoers with specific preferences which require additional marketing tools. Further qualitative analysis of consumers may allow to identify patterns of small segments. However, development of marketing strategies requires an understanding of the most common patterns of theatre behavior, that the model successfully copes with.

References

Abbé-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.

Acquisti, A., & Varian, H. R. (2005). Conditioning prices on purchase history. Marketing Science, 24(3), 367-381.

Baumol, W. J., & Bowen, W. G. (1966). Performing Arts--the Economic Dilemma: A Study of Problems Common to Theatre, Opera, Music and Dance. MIT Press.

Becker, G. S., Grossman, M., & Murphy, K. M. (1991). Rational addiction and the effect of price on consumption. The American Economic Review, 81(2), 237-241.

Bliemer, M. C., & Rose, J. M. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. Transportation Research Part B: Methodological, 44(6), 720-734.

Buzanakova, A.R. & Ozhegov, E.M. (2016). On different approaches to identifying the preferences of theatergoers. Economic Analysis: Theory and Practice, 10, 168-182.

Bonato, L., Gagliardi, F., & Gorelli, S. (1990). The demand for live performing arts in Italy. Journal of Cultural Economics, 14(2), 41-52.

Caussade, S., de Dios Ortúzar, J., Rizzi, L. I., & Hensher, D. A. (2005). Assessing the influence of design dimensions on stated choice experiment estimates. Transportation research part B: Methodological, 39(7), 621-640.

Chashchukhin A.V., Lysenko O.V., Klemeshov A.S. (2015). Portret zritelya opernogo teatra: priglashenie k razgovoru, 91–100. In: Gorod kak stsena. Istoriya. Povsednevnost'. Budushchee. Samara, Media-kniga Publ.

Choi, C., Jeong, M., & Mattila, A. S. (2015). Revenue management in the context of movie theaters: Is it fair? Journal of Revenue and Pricing Management, 14(2), 72-83.

Colbert, F., & Nantel, J. (1989). The market for cultural activities: New approaches for segmentation studies. Cultural Economics ‘88: A Canadian Perspective, 133-140.

Falke, A., & Hruschka, H. (2017). A Monte Carlo study of design-generating algorithms for the latent class mixed logit model. OR Spectrum, 39(4), 1035-1053.

Favaro, D., & Frateschi, C. (2007). A discrete choice model of consumption of cultural goods: the case of music. Journal of Cultural Economics, 31(3), 205-234.

Felton, M. V. (1989). Major influences on the demand for opera tickets. Journal of Cultural Economics, 13(1), 53-64.

Ferrini, S., & Scarpa, R. (2007). Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study. Journal of environmental economics and management, 53(3), 342-363.

Gapinski, J. H. (1984). The economics of performing Shakespeare. The American Economic Review, 74(3), 458-466.

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

Grisolía, J. M., & Willis, K. G. (2012). A latent class model of theatre demand. Journal of Cultural Economics, 36(2), 113-139.

Grisolía, J. M., & Willis, K. G. (2015). Consumer choice of theatrical productions: a combined revealed preference–stated preference approach. Empirical Economics, 50(3), 933-957.

Hansen, T. B. (1997). The willingness-to-pay for the Royal Theatre in Copenhagen as a public good. Journal of cultural economics, 21(1), 1-28.

Hensher, D. A., & Bradley, M. (1993). Using stated response choice data to enrich revealed preference discrete choice models. Marketing Letters, 4(2), 139-151.

Hetrakul, P., & Cirillo, C. (2014). A latent class choice based model system for railway optimal pricing and seat allocation. Transportation Research Part E: Logistics and Transportation Review, 61, 68-83.

Houthakker, H. S., & Taylor, L. D. (1970). Consumer demand in the United States.

Kanninen BJ (2002). Optimal design for multinomial choice experiments. J Mark Res 39:214–217.

Kessels, R., Goos, P., & Vandebroek, M. (2006). A comparison of criteria to design efficient choice experiments. Journal of Marketing Research, 43(3), 409-419.

Laamanen, J. P. (2013). Estimating demand for opera using sales system data: the case of Finnish National Opera. Journal of Cultural Economics, 37(4), 417-432.

Lancaster, K. J. (1966). A new approach to consumer theory. Journal of political economy, 74(2), 132-157.

Lange, M. D., & Luksetich, W. A. (1984). Demand elasticities for symphony orchestras. Journal of Cultural Economics, 8(1), 29-47.

Lévy-Garboua, L., & Montmarquette, C. (1996). A microeconometric study of theatre demand. Journal of cultural economics, 20(1), 25-50.

Lévy-Garboua, L., & Montmarquette, C. (2003). Demand. In: A handbook of cultural economics, Edward Elgar.

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

Moore, T. G. (1966). The demand for Broadway theatre tickets. The Review of Economics and Statistics, 79-87.

Morey, E., & Rossmann, K. G. (2003). Using stated-preference questions to investigate variations in willingness-to-pay for preserving marble monuments: Classic heterogeneity, random parameters, and mixture models. Journal of Cultural Economics, 27(3-4), 215-229.

Morikawa, T., Ben-Akiva, M., & McFadden, D. (2002). Discrete choice models incorporating revealed preferences and psychometric data. In Advances in Econometrics (pp. 29-55). Emerald Group Publishing Limited.

Needleman, L. (1976). Valuing other people's lives. The Manchester School, 44(4), 309-342.

Ozhegova, A., & Ozhegov, E. M. (2017). Heterogeneity in demand for performances and seats in the theatre. Journal of Revenue and Pricing Management, 1-15.

Ozhegova, A., & Ozhegov, E. M. (2018). Estimation of Demand Function for Performing Arts: Empirical Analysis. Journal of the New Economic Association, 37, 82-110.

Ortuzar J. & Willumsen L. (2011). Modelling transport. Wiley, Chichester.

Rose, J. M., & Bliemer, M. C. J. (2006). Designing efficient data for stated choice: accounting for socio-demographic and contextual effects in designing stated choice experiments. In 11th International Conference on Travel Behaviour Research, Kyoto, Japan.

Rose, J. M., & Bliemer, M. C. (2007). Stated preference experimental design strategies. In Handbook of Transport Modelling: 2nd Edition (pp. 151-180). Emerald Group Publishing Limited.

Rose, J. M., & Bliemer, M. C. (2009). Constructing efficient stated choice experimental designs. Transport Reviews, 29(5), 587-617.

Rose, J. M., & Bliemer, M. C. (2012). Sample optimality in the design of stated choice experiments. Travel behavior research in the evolving world, IATBR, India, 119-145.

Rose, J. M., Bliemer, M. C., Hensher, D. A., & Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference alternatives. Transportation Research Part B: Methodological, 42(4), 395-406.

Sandor, Z., & Wedel, M. (2001). Designing conjoint choice experiments using managers’ prior beliefs. Journal of Marketing Research, 38(4), 430-444.

Sándor, Z., & Wedel, M. (2002). Profile construction in experimental choice designs for mixed logit models. Marketing Science, 21(4), 455-475.

Sándor, Z., & Wedel, M. (2005). Heterogeneous conjoint choice designs. Journal of Marketing Research, 42(2), 210-218.

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

Schimmelpfennig, J. (1997). “Demand for ballet: A non-parametric analysis of the 1995 Royal Ballet summer season”. Journal of Cultural Economics, 199-127.

Schulze, G.G., & Rose, A. (1998). Public orchestra funding in Germany–an empirical investigation. Journal of Cultural Economics, 22(4), 227-247.

Swait, J., & Louviere, J. (1993). The role of the scale parameter in the estimation and comparison of multinomial logit models. Journal of marketing research, 305-314.

Throsby, C. D. (1990). Perception of Quality in Demand for the Theatre. Journal of cultural economics, 14(1), 65-82.

Touchstone, S. K. (1980). The effects of contributions on price and attendance in the lively arts. Journal of Cultural Economics, 4(1), 33-46.

Urrutiaguer, D. (2002). Quality judgements and demand for French public theatre. Journal of Cultural Economics, 26(3), 185-202.

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.

Withers, G. A. (1980). Unbalanced growth and the demand for performing arts: An econometric analysis. Southern Economic Journal, 735-742.

Zieba, M. (2009). Full-income and price elasticities of demand for German public theatre. Journal of Cultural Economics, 33(2), 85-108.