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HIGHER SCHOOL OF ECONOMICS

Evgeniy M. Ozhegov, Alina Ozhegova

SEGMENTATION OF THEATRE AUDIENCES: A LATENT CLASS APPROACH FOR COMBINED DATA

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Segmentation of Theatre Audiences: A Latent Class Approach for Combined Data

Evgeniy M. Ozhegov[†], Alina Ozhegova[††]

Abstract

Theatrical productions are perishable goods, since the tickets for a particular play cannot be inventoried and sold after the time of the 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 the Perm Opera and Ballet Theatre and propose marketing instruments to increase theatre revenue. Since the development of a detailed price discrimination strategy requires data on consumer purchase history, behavioral and socio-demographic characteristics, we combine two data sources: data on ticket purchases and survey data. Using a modification of a latent class logit model for joint revealed and stated preference data we identify four segments of the theater's audience. The study reveals theatregoer segments with different willingness-to-pay for performance and seat location characteristics, which allows the development of detailed recommendations on the pricing strategy for various theatre audiences.

Keywords: demand, performing arts, consumer segments, willingness-to-pay.

JEL codes: Z11, C53, D12.

[†]National Research University Higher School of Economics (Perm, Russia). Research fellow, Group for Applied Markets and Enterprises Studies. E-mail: tos600@gmail.com

[††]National Research University Higher School of Economics (Perm, Russia). Young research fellow, Group for Applied Markets and Enterprises Studies. E-mail: arbuzanakova@gmail.com

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 the fact that tickets for a particular play cannot be inventoried and sold after the time of the play. Inflexible capacity is implicated by the limited number of seats in a house. Variable and uncertain demand assumes that the attendance at 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 for decorations, costumes, director's remuneration. Whereas the marginal cost of a particular performance is much lower as marginal cost of additional attendee. These are features of perishable goods.

Price discrimination is widely used in the management of perishable good demand. By virtue of the fact that a theatre audience is heterogeneous in terms of visit purpose, the ability to perceive quality, willingness-to-pay for performance and seat, a price discrimination strategy should take into account the presence of various consumer segments. Furthermore, theatrical productions are a highly differentiated product, possessing 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 the product and its consumers, a theatre with heterogeneous consumers and differentiated performances and seats can use 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 the subject of detailed examination for decades (Moore, 1966; Houthakker & Taylor, 1970; Touchstone, 1980; Gapinski, 1984; Bonato, Gagliardi & Gorelli, 1990; Zieba, 2009). Summarizing the findings, the demand for theatre performances is weakly elastic by price but the estimate of elasticity may vary substantially.

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

The idea of exploring demand in the context of specific seats is supported by the need to account for cross-price elasticity. When the administration increases the price for a ticket, the consumer may not visit the theatre or may switch to another seat with a different price. To utilize a price discrimination policy, theatre administration should recognize the patterns of cross-price elasticity between different seats. This shows how consumers will react to a change in ticket price. The issue of cross-price elasticity between different seats has been poorly investigated in the literature.

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

We study consumers of the Perm Opera and Ballet Theatre, one of best regional musical theatres in Russia. We employ data on online ticket purchases (revealed preferences data, RP). Since the purchase goes through the theatre website, we observe information identifying a consumer, such as name and email. This allows us to analyze the history of audience attendance including frequency, price of tickets, location of seats and performances attended.

Actual data about consumer behavior do not permit the study of cross-price elasticity between seats, since the current pricing policy of the theatre assumes a simultaneous proportional price change for seats. This leads to the problem of price multicollinearity and underidentification of cross-price elasticity. Data on internet purchases also lack socio-demographic consumer characteristics. The absence of consumer characteristics does not allow us to describe consumer segments. Thus, actual data on tickets sales allow the study of real theatre audience behavior but make the identification of cross-price elasticity patterns impossible.

Along with the data on actual consumer choice we collect survey data (stated preferences data, SP). Since we have a database with consumer emails, we conducted an email-based survey. Part of the survey is devoted to a discrete choice experiment, where the respondent is set in a hypothetical situation of choice. As mentioned earlier, the challenge working with actual sales data in the theatre is the absence of price variation within the same price scheme. The choice experiment induces variation in the ticket prices and avoids the issue of price multicollinearity. The inclusion of survey data also makes the dataset richer adding consumer characteristics. This gives insights into consumer segments and preferences towards seats and performance characteristics.

We combine the data from the sales system and surveys which avoids the shortcomings and incorporates the benefits of each data source. Combining datasets, we estimate the price elasticity of demand, theatre audience segments, describe the groups in terms of socio-demographic and behavioral characteristics and propose recommendations for working with these consumer groups.

In order to identify consumer utility from ticket purchases we employ discrete choice models (DCM). These models decompose utility into parts related to production and play characteristics, utility gained from a chosen seat and disutility from ticket price. The estimation of utility function parameters permits an estimation of sensitivity to price change, willingness-to-pay for a particular seat and certain performance characteristics. A particular class of DCM, the latent class model, helps with consumer segmentation by preference, describes consumers by characteristics and provides marketing tools for influencing different consumer groups. We modify LCM for the combined data where the consumer data for segments description may be observed from either RP, SP or both data sources.

The rest of the paper is organized as follows. Section 2 outlines the literature devoted to the theatre demand. Section 3 explains the data. The methodology is discussed in section 4. Sections 5 and 6 describe the empirical results and its managerial implication. Section 7 concludes.

2 Theoretical background

2.1 Research on theatre demand

The empirical literature on theatre demand modelling has evolved since 1960s. In early studies demand was considered mainly as a function of price (Moore, 1966). More sophisticated models include the product characteristics, such as repertory classification, the author, the standard of performance (Throsby, 1990). There is a particular discussion in the literature dedicated to the issue of quality assessment in the demand model (Throsby, 1990; Abbe-Decarroux, 1994; Withers, 1980). The conclusion is that the perception of quality ex-ante is an important determinant for consumers seeking information before purchasing tickets. Then the demand model depends on the 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 (RP) are based on what consumers actually do and employs real purchase data. Stated preferences are used when real data are absent or a survey is the only way to address the research question. Papers based on revealed preferences have better data aggregation. The majority of earlier papers uses data aggregated by 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 estimation results due to the averaged values of variables. Recent studies use more detailed data on theatre attendance. For example, data aggregated by production or particular performances. The use of disaggregated data permits more detailed conclusions about behavior patterns among consumers (Ozhegova & Ozhegov, 2018). The development of DCM makes possible demand modelling using individual data. In the revealed preferences approach demand has different measures, such as the revenue from ticket sales, the number of tickets sold per year, month, the number of tickets sold per performance or the share of tickets sold in the house. In the process of demand modelling, some of the demand measures may pose a difficulty related to the limited capacity of the house. When modelling continuous censored demand, the authors solve the problem of data censorship using the Tobit model, EM method, or imposing different assumptions on demand distribution. For theatre demand, Laamanen (2013) models latent demand using a censored quantile regression, which allows the demand to be upper bounded (Lévy-Garboua & Montmarquette, 2003). In the context of seat choice modeling the availability of seats at the time of purchase needs to be taken into account.

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

Studies based on individual survey data (stated preferences, SP) usually employ discrete choice models that are based on Random Utility Theory (Lancaster, 1966). This is the theory of consumer demand where the utility from a product depends on its attributes and a stochastic term. Then the consumer chooses the variety maximizing her utility. Multinomial (MNL) or binary logit are the simplest models to estimate a 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 MNL – 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 indirect utility or willingness-to-pay. The main drawback of MNL models is the inability to account for unobserved consumer heterogeneity. A mixed logit (MXL) model overcomes this limitation and introduces variation in the utility function parameters estimating the distribution of consumer tastes (Grisolia & Willis, 2015). The particular case of a MXL is a latent class model, where the distribution of utility parameters is discrete and consumers are segmented into the discrete homogeneous groups by their tastes (Grisolia & Willis, 2012).

Both RP and SP approaches have strengths and weaknesses. RP is based on real purchase behavior of consumer, which is 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 to parameter under-identification. The SP approach can solve this problem using discrete choice experiments, so that a small sample may ensure sufficient variation in the data. Combining RP decisions made in real conditions and SP choices made under hypothetical conditions can overcome the shortcomings of the approaches. Choice experiments address the issue of insufficient variation in attributes and data on real behavior induces realism into the model. Grisolia & Willis, 2015 demonstrate the advantages of the combined RP-SP data method in identifying consumer preferences for performance characteristics.

In this article, we focus on the model of individual choice 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 for each segment, and patterns of switching for the segments depending on the performance characteristics.

2.2 Research on experimental design

In the context of SP data collection, stated choice experiments are mostly used for the description of consumer behavior. This kind of experiment relies on underlying experimental designs. This part of the 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 the observed choice made in the experiment. The allocation of attribute levels over the choice sets has a key role in the 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).

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

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

The next feature of a SC experiment is the number of attribute levels. For a continuous variable the number of attribute levels is given by the model specification. A wide attribute level range is statistically preferable since the results are more effective. The number of levels is predetermined, if the attribute is coded as the number of dummies.

Finally, when the attributes and attribute levels are chosen, one is able to generate the experimental design. Full factorial design includes all possible choice situations. Practically, the number of all possible choice situations is too large. Therefore, a fractional factorial design – a subset of choice situations - is used. The procedure of generating choice situations in a fractional factorial designs is the same. It starts with generating the full factorial design, then taking a subset of choice situations relying on the criterion of optimality. Random factorial design is a possible way of choosing choice situations, but is expectedly not the best. An orthogonal design is one of the best known ways of choosing the choice situation subset. Taking the situation in the resulting design, it minimizes 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 the independent evaluation of the parameters of characteristics. However, the minimization of the correlation between attributes does not ensure the effectiveness of estimation. Hence, recent research has suggested another type of factorial design – efficient design. This type of fractional factorial design maximizes the information extracted from each choice situation. Technically, it seeks a design with efficient estimates in terms of predicted standard errors of the resulting parameters (Sándor & Wedel, 2001; Sándor & Wedel, 2002; Sándor & Wedel, 2005). Traditionally efficient designs require prior knowledge about the asymptotic variance-covariance (AVC) matrix. Priors allow a better distribution of attribute levels in the design. Prior knowledge may come from previous literature, pilot studies or consumer behavior theory.

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

Research has begun to use designs without prior parameters of the AVC matrix. In these cases, prior parameters are drawn from a Bayesian parameter distribution. Bayesian efficient designs get rid of the necessity to make priors and, consequently, are robust to errors in prior settings (Ferrini & Scarpa, 2007). Since there is no previous research about the tastes of Perm Opera and Ballet Theatre consumers, there is no prior information about the distribution of parameters available. In this research we use a Bayesian D-efficient design to construct a choice experiment that is efficient in the resulting parameter estimates and robust to the choice of the priors for the parameters (Falke & Hruschka, 2017).

3 Methodology

Both the RP and SP approaches for the identification of consumer preferences are based on random utility theory (Lancaster, 1966). It states that utility for a certain consumer is determined by the 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 the utility function may be written as:

$$U_{ijt} = V_{ijt} + \epsilon_{ijt} = x_{ijt}\beta + \epsilon_{ijt}, \tag{1}$$

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

To estimate the taste parameters a consumer is considered 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) with $EV\ I$ (Gumbel) distribution with variance normalized to 1, the model takes the form of a Multinomial Logit (MNL). According to McFadden (1974), the probability that consumer i chooses alternative j in choice situation t in a MNL model is given by:

$$P_{ijt} = \frac{e^{x_{ijt}\beta}}{\sum_{q} e^{x_{iqt}\beta}}. \tag{2}$$

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

$$L(y, x|\beta) = \prod_{i} \prod_{j} \prod_{t} P_{ijt}^{y_{ijt}} \tag{3}$$

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

There are two ways to relax 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 the 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).

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

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

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

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

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

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

The latent class as a 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. The latent class model may be presented as the sum of MNL models adjusted for the mass of each class, then the probability of choice is expressed by the sum of conditioned probabilities weighted by the probability of belonging to each class (the size of class in population):

$$P_{ijt} = \sum_m S_{im} \frac{e^{x_{ijt}\beta_m}}{\sum_q e^{x_{iqt}\beta_m}}, \tag{6}$$

where S_im is the probability of individual i belonging to the class m. This also allows us to model the probability of consumer membership of a certain class and describe the classes in terms of their socio-demographic characteristics. The probability of belonging to a class S_{im}

also takes the form of multinomial logit:

$$P_{ijt} = \sum_m \frac{e^{d_i\gamma_m}}{\sum_s e^{d_i\gamma_s}} \frac{e^{x_{ijt}\beta_m}}{\sum_q e^{x_{iqt}\beta_m}}, \tag{7}$$

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

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 the problem of finding a global maximum is solved by the maximization of the likelihood function with respect to both β and γ simultaneously. Since this approach is usually cumbersome by virtue of the complex structure of the objective function and the presence of multiple maxima, the EM algorithm with a sequential iterative maximization of parameters β and γ in equation (7) is applied. This procedure works slower compared to the previous approach and provides less efficient estimates but leads to proper estimates more often.

Since the processes of generating of RP and SP data differ, utility functions also have some differences. Given the information about the source of data we may write equation (1) for a 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 the utility function for RP data as:

$$U_{ijt}^{RP} = x_{jt}^{RP}\beta^{RP} + x_t^{RP}\theta_j^{RP} + \alpha \ln p_{jt} + \mu_j + \epsilon_{ijt}^{RP} \tag{8}$$

where U_{ijt}^{RP} is a utility function that explains the 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 (the percentage 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 the log of ticket prices, μ_j is an alternative (seating area) specific constant, ϵ_{ijt} is a Gumbel $i.i.d.$ error term.

While the experiment of discrete choice is designed to repeat the situation of real ticket choice, then the utility function for SP data has the same structure as the RP one, but differs in the set of attributes:

$$U_{ijt}^{SP} = x_{jt}^{SP}\beta^{RP} + \alpha \ln p_{jt} + \mu_j + \epsilon_{ijt}^{SP} \tag{9}$$

$$U_{i0t}^{SP} = \mu_0 + \epsilon_{i0t}^{SP}$$

where U_{ijt}^{SP} is a utility function that explains the choice of consumer i from alternative j in the choice situation t, x_{jt}^{SP} are the characteristics which vary across alternatives within a choice set (characteristics of performance). The zero index for alternatives represents an option to choose none of the proposed alternatives in a particular choice set. This alternative contains no observed characteristics which may explain the choice, has a 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 structures and a common subset of parameters (sensitivity to price 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 the identification of common parameters one should account for parameter estimates normalized to the variance of the error term. When the true variance of the error term in utilities given in (8) and (9) are under-identified, matching RP and SP, and the joint identification of common parameters requires the scaling of the SP (or RP) part to parameter ρ. The scale parameter reflects the ratio between the true but unobserved ratio of error variances between RP and SP data. Generally, this ratio is not equal to 1 because of the 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 the utility function for joining RP and SP choice may be represented as:

$$\begin{cases} U_{ijt}^{RP} = x_{jt}^{RP}\beta^{RP} + x_t^{RP}\theta_j^{RP} + \alpha \ln p_{jt} + \mu_j + \epsilon_{ijt}^{RP} \\ \rho U_{ijt}^{SP} = \rho(x_{jt}^{SP}\beta^{RP} + \alpha \ln p_{jt} + \mu_j + \epsilon_{ijt}^{SP}) \\ \rho U_{i0t}^{SP} = \rho(\mu_0 + \epsilon_{i0t}^{SP}) \end{cases} \tag{10}$$

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

Then one may estimate a full set of parameters for the MNL model (10) under the assumption of heteroscedastic across types of data $EV\,I$ distribution of joint error ϵ_{ijt}. According to equation (2), the probabilities of observed choice may be written for RP and SP data separately as:

$$P_{ijt}^{RP} = \frac{e^{x_{jt}^{RP}\beta^{RP} + x_t^{RP}\theta_j^{RP} + \alpha \ln p_{jt} + \mu_j}}{\sum_q e^{x_{qt}^{RP}\beta^{RP} + x_t^{RP}\theta_q^{RP} + \alpha \ln p_{qt} + \mu_q}} \tag{11}$$

$$P_{ijt}^{SP} = \frac{e^{\rho(x_{jt}^{SP}\beta^{SP} + \alpha \ln p_{jt} + \mu_j)}}{e^{\rho\mu_0} + \sum_q e^{\rho(x_{qt}^{SP}\beta^{SP} + \alpha \ln p_{qt} + \mu_q)}}$$

Given the probabilities of choices, model (11) may be estimated via full information maximum likelihood (FIML) for the likelihood function in the following form:

$$L(y, x, p|\beta, \theta, \alpha, \mu, \rho) = \prod_i \prod_{t\in RP} \prod_j (P_{ijt}^{RP})^{y_{ijt}} \prod_{t\in SP} \prod_j (P_{ijt}^{SP})^{y_{ijt}} \tag{12}$$

The maximization of likelihood function (12) requires a pre-step of scale parameter ρ estimation. In order to estimate the 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 β_b^{RP}, θ_b^{RP}, α_b^{RP}, μ_b^{RP} maximizing RP part of (13) 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 β_b^{SP}, α_b^{RP}, μ_b^{RP} maximizing SP part of (13) only. Thus, we obtain B collections of RP parameters ξ_b^{SP}.

3. On intersected subset (α and μ_j) of collections of RP and SP estimated parameters obtained from bootstrap samples one may estimate ρ by OLS from the equation:

$$\xi_b^{RP} = \rho \xi_b^{SP} + \eta_b, \tag{13}$$

where η_b is $i.i.d.$ error vector.

In order to identify and describe consumer segments we generalize choice model (10) in a latent class fashion. Let d_i^{RP} be the set of behavioral consumer characteristics available from RP data and d_i^{SP} be the 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 i being a member of latent class m under the logit assumption may be represented as:

$$S_{im} = [\frac{e^{d_i^{RP}\gamma_m^{RP}+\kappa_m^{RP}}}{\sum\limits_s e^{d_i^{RP}\gamma_s^{RP}+\kappa_s^{RP}}}]^{1-I_i^{SP}} \times [\frac{e^{d_i^{SP}\gamma_m^{SP}+\kappa_m^{SP}}}{\sum\limits_s e^{d_i^{SP}\gamma_s^{SP}+\kappa_s^{SP}}}]^{1-I_i^{RP}} \times [\frac{e^{d_i^{RP}\gamma_m^{RP}+d_i^{SP}\gamma_m^{SP}}}{\sum\limits_s e^{d_i^{RP}\gamma_s^{RP}+d_i^{SP}\gamma_s^{SP}}}]^{I_i^{RP}I_i^{SP}} \tag{14}$$

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

Equation (14) models the probability of belonging to a class m for the three possible cases. The first term of the sum makes a contribution to the membership probability if only RP data for individual i is observed. The second term of the 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 β_m, θ_m, α_m, μ_m are parameters of th choice model (10) utility function for an individual belonging into class m, then the choice probabilities for individual i may be written as:

$$P_{ijt}^{RP} = \sum_m S_{im} \frac{e^{x_{jt}^{RP}\beta_m^{RP}+x_t^{RP}\theta_{jm}^{RP}+\alpha_m \ln p_{jt}+\mu_{jm}}}{\sum\limits_q e^{x_{qt}^{RP}\beta_m^{RP}+x_t^{RP}\theta_{qm}^{RP}+\alpha_m \ln p_{qt}+\mu_{qm}}} \tag{15}$$

$$P_{ijt}^{RP} = \sum_m S_{im} \frac{e^{\rho(x_{jt}^{SP}\beta_m^{SP} + \alpha_m \ln p_{jt} + \mu_{jm})}}{e^{\rho\mu_{0m}} + \sum_q e^{\rho(x_{qt}^{SP}\beta_m^{SP} + \alpha_m \ln p_{qt} + \mu_{qm})}}$$

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

$$L(y, x, p|\beta, \theta, \alpha, \mu, \gamma, \kappa, \rho) = \prod_i \prod_{t \in RP} \prod_j (P_{ijt}^{RP})^{y_{ijt}} \prod_{t \in SP} \prod_j (P_{ijt}^{SP})^{y_{ijt}}. \tag{16}$$

4 Data description

Data for this research were collected from people attending plays at the Perm Opera and Ballet Theatre. 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. The theatre performs around 200 shows per year, 40 of which are unique productions and 3-5 are new productions per year.

The Perm Opera and Ballet Theatre is a non-commercial organization and as such is loss-making. As of 2016, the Perm state budget covers around 75% of expenses, 17% comes from income from ticket sales, and 8% 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 mechanisms and charging different prices for different performances and seats.

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

4.1 Revealed preferences data

Revealed preferences data are taken from the ticket sales system, provided by the theatre administration. The dataset includes information on tickets purchased for the six seasons between August 2011 and July 2017. During this time the Perm theatre showed 966 plays of 160 unique productions. Since the shows at the theatre are highly differentiated, as are the 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 represents the ticket price in rubles across seating areas

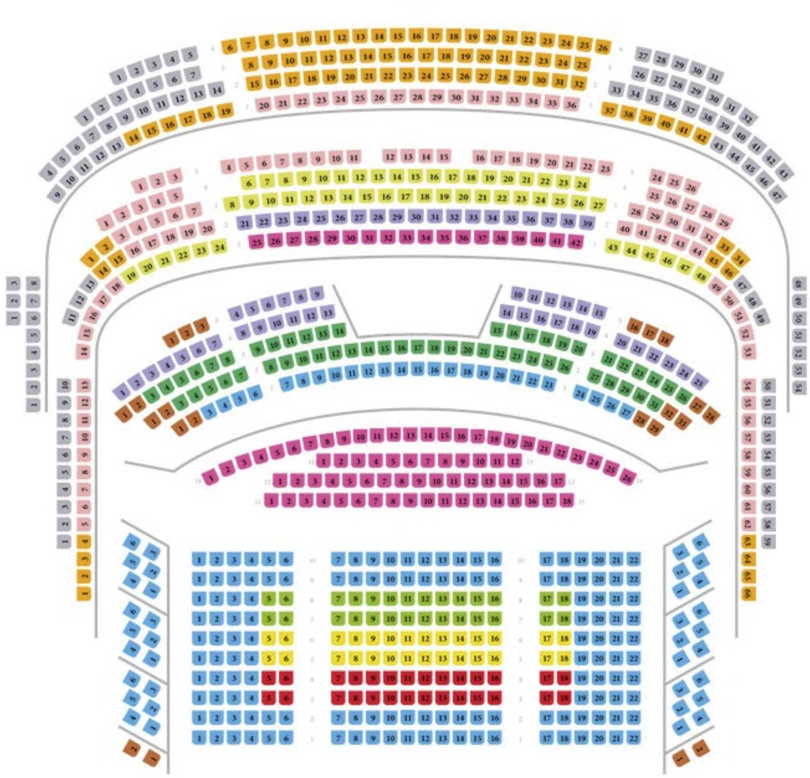

Fig. 1. Scheme of a house

for all performances analysed. 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 seat. The house of the theatre has some ways to be divided into seating areas. One plan of the house which covers around 70% of performances and brings 90% of total revenue. The analysis here is focused on performances with this plan, which ensures the homogeneity of the data collected.

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, performing plays in tour halls. In this paper, we confine our analysis to the plays that showed at the main venue.

The study includes only operas and ballets, since these types of shows possess similar characteristics allowing the estimation of the contribution of a particular performance attribute. Thus, given these limitations RP data include information for 210 plays, 40 of which were unique productions.

For plays included in the analysis, we collect information on performance characteristics which explain 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), include information on the composer and construct a dummy for the nationality of the author

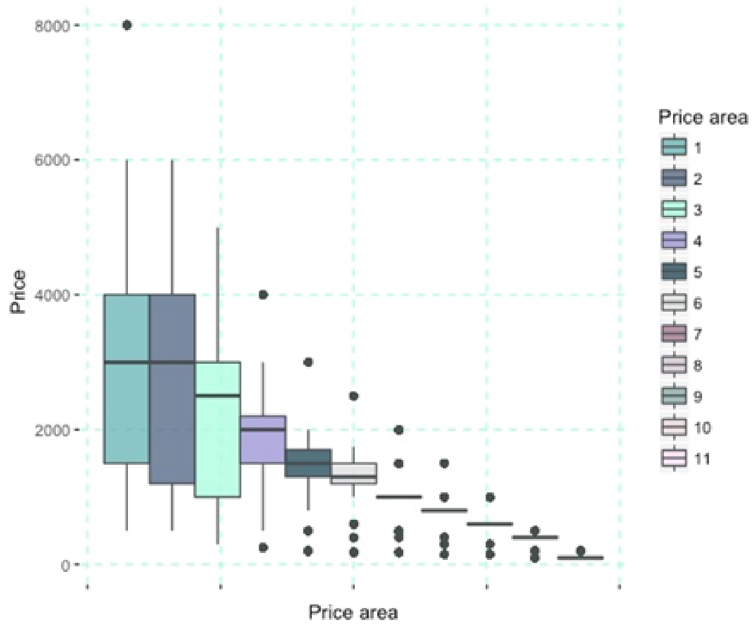

Fig. 2. Distribution of ticket price across seating areas

(Russian/foreign) and a 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 estimates 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). The 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 the 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 shows the descriptive statistics for performance characteristics. 45% of performances are ballets, the rest (55%) are operas. 61% are included in the ratings of the best operas or ballets respectively. 20% have at least one nomination for a Golden Mask award (Buzanakova & Ozhegov, 2016).

There are two main ways that customers purchase tickets: through the booking office and the website of the theatre. Consumers, 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 are carried out online and the proportion is steadily growing. In the study, we focus on online purchases, since these transactions store information not only about the tickets bought, but also about the buyer, minimally the email address. Regardless of sales channel consumer has the same set of available tickets, there is no

Tab. 1 Descriptive statistics for performance characteristics

Variable	Obs	Mean	St. 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

challenge with choice set recovery. Table 2 shows the descriptive statistics for online and offline purchases. Offline and online buyers demonstrate different preferences related to performance characteristics.

Thus, online buyers prefer ballet rather than opera, productions with nominations for a Golden Mask, more often visit plays with Currentzis as a conductor and premiere plays. Online buyers buy tickets 32 days before the performance on average, which is less than for offline buyers. The average price of online purchases does not differ from average price of offline purchases. Nevertheless, differences in preferences do not allow us to extend the conclusions made on online transactions to the whole set of sales.

Focusing on online purchases we collect information about the ticket purchased. This includes the name of performance, date and time of the performance (season, year, month, day of week, hour), the list price of the ticket, the actual price of the purchase (after discounts), the 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 60,000 transactions. The mean price of a ticket is around 1000 rubles. The average attendance at the time of purchase is 44%. The majority of tickets were bought in advance. Two thirds of tickets are bought approximately 1-2 months before the performance, 20% about 3 months before the play. Only 10% of tickets are purchased in the week of the play.

Since we have an extensive time period in data on online purchases, we can also reconstruct the history of purchases including all the transactional information described above. The data include information on buyer ID, date of purchase, performances attended, number of tickets

Tab. 2 Comparison of mean tickets characteristics for offline and online purchases

Variable	All tickets (59919 obs.)	Offline Purchases (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, rub.	1064.2	1045.7	1084.1	-38.3
Attendance	0.437	0.427	0.447	-0.021
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***
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***
				$\chi^2(32) = 55.4$, p-value $= 0.006$

Notes: Table cells represents mean values. 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.

Tab. 3 Descriptive statistics for chosen tickets

Variable	Obs	Mean	St. Dev.	Min	Max
Price, rub.	59919	1064.2	946.9	100	8000
Attendance	59919	0.441	0.268	0	0.994
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
Online purchase	59919	0.481	0.499	0	1
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

purchased and the average price of purchases. Table 4 represents the behavioral characteristics of online buyers. The average internet buyer has purchased tickets online 2.4 times. The average number of tickets purchased through the internet is 5.2. On average the buyer purchases 2.3 tickets per order. 83% of buyers demonstrate strong preferences for groups of seats buying all tickets to the same group of seats.

4.2 Stated preferences data

The second source of data for the research is an online survey. The respondents who made online purchases received an email inviting them to complete the survey. The email was sent from the theatre as a standard promotional letter. The online-survey has two parts. The first is dedicated to the discrete choice experiment (DCE). This is a source of data about choices 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 the qualitative study of theatregoers. Alternatives are described by the type of performance, premiere play or not, adaptation, conductor, seating area and ticket price (Table 5). The consumer chooses one alternative per card out of three hypothetical alternatives and option to choose none of the above. Relying on previous research where authors

Tab. 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

Variable	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

Tab. 5 Attributes and levels in discrete choice experiment

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

found that the optimal number of choice sets to be shown is between 6 and 13, we offer each respondent 10 sets to choose from (Caussade *et al.*, 2005).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 productions that are usually presented in the theatre: opera and ballet. Premiere reflects whether the productions is new or the performance has been showing for some time (as part of the regular repetoire). Adaptation (modern or traditional) describes the interpretation of the work. Traditional adaptations reflect that director sought to stage the play as close as possible to the original work. Modern adaptation assumes non-standard approach to the production. The conductors were chosen for the highest fraction of plays conducted. Prices were also chosen based on real pricing strategy for seating areas in the current theatre season. Once the attributes and levels of attributes were set, we produce the experimental design to determine the combination of attribute levels for each choice alternative.

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

Tab. 6 Comparison of chosen and unchosen alternatives' characteristics in SP data

Variable	All alternatives (29940 obs.)	Chosen alternatives (7560 obs.)	Unchosen alternatives (22380 obs.)	Difference
Price	2979.2	2043.1	3295.4	-1252.3***
Ballet	0.50	0.56	0.49	0.07***
Premiere	0.49	0.52	0.48	0.04**
Modern	0.50	0.50	0.50	0.00
Conductor: Currentzis	0.25	0.37	0.22	0.15***
Conductor: Platonov	0.23	0.20	0.24	-0.04*
Conductor: Abashev	0.26	0.23	0.26	-0.03*
Conductor: Urupin	0.25	0.19	0.28	-0.09***
Seating area 1	0.09	0.06	0.09	-0.03***
Seating area 2	0.08	0.08	0.08	0.00
Seating area 3	0.09	0.09	0.08	0.01
Seating area 4	0.08	0.10	0.08	0.02*
Seating area 5	0.12	0.13	0.12	0.01
Seating area 6	0.11	0.12	0.11	0.01
Seating area 7	0.10	0.10	0.11	-0.01
Seating area 8	0.10	0.12	0.09	0.03**
Seating area 9	0.10	0.10	0.09	0.01
Seating area 10	0.09	0.06	0.09	-0.03***
Seating area 11	0.04	0.03	0.05	-0.02***
				$\chi^2(19) = 47.5$, p-value = 0.003

Notes: Stars in the difference column corresponds to p-value of t-test for the difference between chosen and unchosen alternative characteristic mean.
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.

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

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

Table 6 allows us to impose a hypothesis about theatregoer preferences for alternative characteristics. The alternatives chosen are cheaper than those not chosen. Among performance characteristics respondents are likely to choose ballets rather than operas, premiere plays rather than the regular repertoire, Currentzis over other conductors and central seats among seating areas. These findings correspond to the outcomes of the preliminary RP data analysis that predict the absence of bias in SP responses.

The second part of the online survey includes questions about socio-demographic status and the cultural participation of respondents. Table 7 describes the respondents in terms of their residence, gender, age, education, income and other characteristics. The majority of respondents are Perm residents while 17% live outside the Perm region. This fact is described by phenomenon of “cultural tourism”, when travelling people visit cultural events. 80% of respondents are female which corresponds exactly to the real gender proportion of theatre visitors according to internal theatre surveys. The average respondent is 40 years old, married or with a partner, has higher education and has white-collar work, which is also consistent with internal theatre surveys. The majority of respondents have a monthly income between 15 and 29,000 rubles (according to the portal of Perm statistics the official average wage in Perm in 2016 is 28,000 rubles). A question on the reason for the visit allows multiple answers while other questions (constructed variables) allow single option only.

5 Empirical results

The empirical results are arranged in accordance with the data description. The first part of this section is dedicated to a discussion of estimation results based on RP and SP data separately. Then we discuss the results on combined the RP/SP dataset.

First of all, we test, whether the results based on online sales may be generalized to a whole set of purchases. Therefore, we estimate the MNL model on the data for offline and online purchases (Table 8). Since the correct estimation of price sensitivity is crucial for the development of a 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 which leads to the necessity of adjusting the pricing strategy to a greater degree in relation to online sales.

Table 9 represents detailed regression results from the MNL 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 the choice of a ticket from a certain seating area at a performance. The key finding in column 4 of Table 9 is that online purchasers are price sensitive 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 comparisons. The changes in price sensitivity across the columns in Table 9 show the need to account for seat quality, performance and consumer characteristics.

The RP-based choice model does not allow the identification of the probability of the null alternative, which reflects either the choice of another performance or the choice not to go to the

Tab. 7 Socio-demographic characteristics of online buyers

Variable	Obs	Mean	St. 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 100 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

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

	(1) All tickets	(2) Offline purchases	(3) Online purchases
Log. of Price	-0.272***	-0.145**	-0.432***
	(0.035)	(0.051)	(0.050)
Number of observations	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

Notes: 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.

Tab.9 Logit results for online purchases

	(1)	(2)	(3)	(4)
Log. of 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 observations	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

Notes: Standard errors in parentheses.

Significance levels are * - $p < 0.05$, ** - $p < 0.01$, *** - $p < 0.001$.

Tab.10 Results for multinomial logit models on SP data with different set of controls

	(1)	(2)	(3)
Log. of Price	-0.017***	-0.310***	-0.323***
	(0.003)	(0.012)	(0.013)
Controls:			
Seating area dummies	-	+	+
Performance characteristics	-	-	+
Number of observations	39920	39920	39920
Number of choice sets	9980	9980	9980
Number of parameters	1	12	18
Log. Likelihood	-20102.4	-19654.8	-19205.0
BIC	40215.5	39436.7	38600.7

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

theatre. We cannot perform a proper analysis of the cross-price elasticity of demand for seating areas on the RP data, since we may only predict a change in the share of bought tickets across seating areas but not a change in the mass of tickets in general. Finally, the RP behavioral data give insufficient description about the segments, which does not allow us to compare the results with those in the literature or to develop marketing strategies. These factors emphasize the use of SP data.

The estimation results of MNL models on SP data is in Table 10. The SP model includes only the type of show (opera/ballet), an indicator of whether the production is premiere, the adaptation (modern/traditional), the conductor (Currentzis, Abashev, Platonov, Urupin), seating area (from 1 to 11) and price. Alternative specific constants represent different price area quality as in the RP data. In each regression, the dependent variable is a latent utility from the choice of a ticket from a proposed set of three tickets and the null alternative. Table 12 shows the regression results adjusted for the performance characteristics listed above and alternative specific constants. The increase in the price sensitivity estimate means these variables need to be accounted for.

Table 11 represents detailed regression results from the MNL model on the RP, SP and combined RP-SP data sets. In each regression, the dependent variable is the utility gained from the chosen seating area. The regressions in the table include the log of the price, the seating area, and other control variables. The discrete choice experiment does not include the seating area at the time of purchase, this parameter is not estimated in the SP part (column 2 in Table 11). The differences in the number of observations in regressions is explained by the different data generating processes. Finally, the log likelihood of the three models is not directly comparable because of differences in sample size and the number of estimated parameters. The model on joint RP-SP data requires the prior estimation of scale parameter ρ. The estimate of ρ based on 100 bootstrap replications of the RP and SP data sets over the choice sets is 0.888. As it statistically differs from 1, one may conclude that SP data has higher unexplained utility variance compared to RP data.

Generally, the models can be compared in terms of standard error values. Since the efficient experimental design allows us to induce more variability in the 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 11, the regression results of the model on joint RP-SP data is reported. The estimates obtained on joint RP-SP data are in the interval between the RP and SP (adjusted by estimate of ρ) parameters which is consistent with the estimation procedure. RP-SP estimates have smaller standard errors compared to both the RP and SP results and, consequently, more variables have a statistically significant impact on choice, including price. The RP-SP model is also preferred over either the SP or the RP, since by construction it includes the actual choice made by individuals and by virtue of the efficient experimental design, provides more efficient estimates of the parameters.

Table 12 presents results for the latent class model with various number of classes calibrated on joint RP-SP data. Since, as the number of classes increases, the 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), which demonstrates, whether it is worthwhile increasing the complexity of the model by adding additional latent classes. According to Table 12 we may conclude that the model with four classes performs better in terms of the log likelihood and BIC criteria. The model with five classes fails to converge to global maximum, which points at impossibility dividing the sample by the higher number of statistically different classes. Therefore, we interpret and analyze classes according to the model with four classes.

The model of class membership (Table 13) describes the differences in classes with respect to class 1. The results reveal that all the variables included in the class membership model are significant, thus, the classes statistically differ from each other by these characteristics. For the socio-economic characteristics, theatregoers from the most sensitive to price change segment (column 1) purchase the cheapest tickets on average. However, they stand out by the longest 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 frequent ballet attendance. Among conductors they do not demonstrate loyalty to particluar one. They usually prefer to purchase tickets in back seating areas (from 8 to 11), which are sold at a lower price. The most sensitive segment shows the least sensitivity to the seating area. Purchasing the ticket, they have to choose between an affordable price and the

Tab.11 Comparison of logit results for RP, SP and joint RP and SP data

	(1) RP data	(2) SP data	(3) Joint RP and SP data
Log. of Price	-0.602***	-0.323***	-0.409***
	(0.041)	(0.013)	(0.012)
Attendance	-0.863***	-	-0.709***
	(0.044)		(0.040)
Seating area 0	-	-1.793***	-2.019***
		(0.124)	(0.115)
Seating area 2	0.187	0.342***	0.299***
	(0.130)	(0.072)	(0.063)
Seating area 3	0.293*	0.334***	0.335***
	(0.125)	(0.071)	(0.055)
Seating area 4	2.067***	0.514***	1.295***
	(0.102)	(0.071)	(0.055)
Seating area 5	1.383***	0.382***	0.873***
	(0.109)	(0.067)	(0.057)
Seating area 6	0.622***	0.256***	0.544***
	(0.118)	(0.068)	(0.060)
Seating area 7	0.737***	0.063	0.489***
	(0.119)	(0.070)	(0.062)
Seating area 8	0.673***	0.324***	0.660***
	(0.121)	(0.070)	(0.062)
Seating area 9	1.135***	0.052	0.723***
	(0.117)	(0.073)	(0.059)
Seating area 10	0.301*	-0.483***	0.047
	(0.127)	(0.078)	(0.063)
Seating area 11	0.196	-0.712***	0.296***
	(0.153)	(0.095)	(0.068)
Number of observations	300712	39920	340632
Number of choice sets	28380	9980	38260
Number of parameters	52	18	59
Log. Likelihood	-59543.1	-19205.0	-79267.9
BIC	119524.1	38600.7	159287.4

Notes: 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. Seating area 1 is base category.

Tab.12 Latent class logit results for joint RP and SP data

	Number of classes			
	1	2	3	4
Weighted average parameter:				
Log. of Price	-0.409***	-0.394***	-0.392***	-0.396***
	(0.012)	(0.011)	(0.013)	(0.016)
Attendance	-0.709***	-0.862***	-0.772***	-0.641***
	(0.040)	(0.042)	(0.050)	(0.085)
Class 1:				
Log. of Price	-	-0.345***	-0.316***	-0.744***
		(0.010)	(0.011)	(0.020)
Attendance	-	-0.907***	-0.319***	-0.504***
		(0.039)	(0.032)	(0.144)
Class share		0.567	0.330	0.144
Class 2:				
Log. of Price	-	-0.459***	-0.549***	-0.321***
		(0.012)	(0.019)	(0.013)
Attendance	-	-0.803***	-1.097***	-0.654***
		(0.048)	(0.064)	(0.085)
Class share		0.433	0.304	0.372
Class 3:				
Log. of Price	-	-	-0.331***	-0.448***
			(0.013)	(0.017)
Attendance	-	-	-0.908***	-0.626***
			(0.058)	(0.082)
Class share			0.367	0.244
Class 4:				
Log. of Price	-	-	-	-0.252***
				(0.012)
Attendance	-	-	-	-0.715***
				(0.098)
Class share				0.241
Number of observations	340632	340632	340632	340632
Number of choice sets	38260	38260	38260	382600
Number of parameters	59	59	59	59
Log. Likelihood	-79267.9	-68312.5	-61873.2	-59665.6
BIC	159287.4	138637.7	127032.9	123891.6

Notes: Significance levels are * - $p < 0.05$, ** - $p < 0.01$, *** - $p < 0.001$.

best location of the seat. Since the most attractive seats in terms of price and location are purchased faster, representatives of class 1 sacrifice convenience in favor of affordable price. From the point of socio-demographic characteristics class 1 includes people who live in Perm region, are unmarried or not in a relationship and have higher education. The most sensitive respondents possess the lowest income compared to the rest of audience. This class also younger people in contrast with those in other classes. We also may call them as "higher sophisticated" spectators, since they are well informed about the repertoire of the theatre. At the same time, people from class 1 more often visit performances at other Perm theatres, which in some sense is an indicator of an omnivorous range of tastes. Lastly, the majority mention "educational" as the main goal of the theatre visit. This class is thin and accounts for 14.4% of spectators.

Class 2 is similar in many respects to class 4 (column 4 in Table 13). They are also less sensitive to price change and more sensitive to seat location compared to class 1. They differ from the rest by the second highest mean price of ticket purchased. In comparison with other classes they acquire the most number of tickets in an order, thus, they tend to attend the theatre with others. This class usually purchase tickets in advance which 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). The highest income and preferences for the most popular performances and the most expensive seats mark the class as representing more affluent attendees. The mixed structure of class 2 is reflected in some socio-demographic and behavioral characteristics. The class is characterized by a shorter history of online purchases. Among all segments, people who visit the theatre more than four times a year are more found in the class. 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 the mixed structure of class. People who attend the theatre from 1 to 4 times a year are also more common 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 statistically insignificant in terms of price sensitivity. Class 2 is also characterized by a low level of sophistication which may be associated with the significant share of people from other regions. Class 2 demonstrates the highest attendance of other Perm theatres. This class is the most numerous and contributes 37.2% of the theatre market. Class 2 also includes people who demonstrate the same reaction to price change, but differ in their socio-demographic and behavioral description. The class includes some small consumer groups, who differ from the rest of the class, and whose characteristics cannot be attributed to the whole segment, requiring separate consideration, since their characteristics prescribe the use of distinctive marketing tools of influence. People from other regions constitute only 17% of the whole theatre audience, and their group size does not allow us to consider them as a separate segment. Nevertheless, the analysis reveals that they do not differ statistically 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. 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.

Representatives of class 3 (column 3 in Table 13) differ from other segments only by their infrequent visits to new productions, otherwise they look like the average audience of the theatre. They equally prefer operas and ballets, purchase tickets in the middle of the house. The majority of people in this class are residents of Perm, married, have an intellectual job and average income. They demonstrate high theatre attendance (1 - 4 times a year) compared to other segments, purchase through theatre ticket office and visit the theatre with family members. This class accounts for 24.4% of theatre audience.

Class 4 includes representatives of the least sensitive segment in terms of price effect (column 4 in Table 13). They expectedly purchase more expensive tickets on average than the other three classes. However, the average income of respondents in the class is not the highest among segments and is lower than the income of classes 2 and 3. Among performances they prefer ballet rather than opera, which is consistent with the fact that the prices for ballet are noticeably higher than the prices for operas. They equally visit premieres and the regular repertoire, plays conducted by Currentzis and other conductors. This class is characterized by preferences for seats in the middle of the house, which are the best seats for enjoying the ballet. They demonstrate the highest sensitivity to the 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 more for a better seat. Low sensitivity to price changes and a high willingness-to-pay for good seats may be associated with the low frequency of visits. The main goals of theatre visit is to go out and have fun. This class is characterized by the highest sophistication among theatre audiences. The share of this class constitutes 24.1% of theatre audience.

6 Practical implication

Finally, segmenting theatre audiences and identifying their preferences allows us to develop practical recommendations for increasing the effectiveness of pricing using price discrimination methods. In theory, the methods of price discriminations, setting a different price schedule for each individual, allows 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 each consumer's reservation price. Nowadays large datasets on individual

Tab.13 Results for class membership model on joint RP and SP data

Variable	Class			
	1	2	3	4
Log of average price of purchase		0.321***	0.211***	0.444***
Log of number of tickets purchased		-0.805***	-0.606***	-0.399***
Log of average number of tickets in order		0.729***	0.535***	0.308***
Share of premiere plays		0.066**	-0.571***	-0.024
Share of plays with Currentzis		0.824***	0.333***	0.023
Share of ballets		-1.243***	-0.057	0.547***
Share of tickets in 5-7 seating areas		-0.235***	0.898***	0.448***
Share of tickets in 8-11 seating areas		-1.124***	-0.633***	-0.352***
Place of residence: Perm region		-0.436***	-1.003***	-0.096*
Place of residence: other		2.323***	-0.039	-0.032
Gender: Female		1.532***	0.984***	0.021
Age of respondent		0.206***	0.053*	0.128***
Age of respondent sq.		-0.076*	-0.009	-0.046*
Family status: Married or coupled		1.413***	0.889***	0.158***
Education: some college		2.491***	1.679***	0.381***
Education: PhD		-2.409***	-1.581***	-0.389***
Job: have subordinaries		1.012***	0.373***	0.371***
Job: intellectual		-0.616***	0.834***	0.432***
Category of income		0.521***	0.105***	0.046**
Income: no answer		1.256***	0.791***	0.063***
Visits per year: 1-4		1.602***	0.828***	-0.539***
Visits per year: more than 4		0.835***	0.534***	-0.228***
Time to purchase: in a month to play		1.511***	1.205***	0.458***
Time to purchase: in two months to play		2.066***	0.394***	-0.317***
Time to purchase: no answer		-0.349***	0.319***	0.961***
Sophistication: high		-0.561***	-0.297***	0.591***
Visit other theaters		0.232***	-1.342***	-0.212***
Goal of visit: educational		-1.717***	-0.647***	-0.339***
Goal of visit: go out		-0.819***	-0.925***	0.538***
Goal of visit: have fun		0.271***	-0.619***	0.522***
Constant		0.997***	0.567***	0.846***
Parameters in latent class model:				
Log. of Price	-0.744***	-0.321***	-0.448***	-0.252***
Attendance	-0.504***	-0.654***	-0.626***	-0.715***
Class share	0.195	0.288	0.314	0.203

Notes: Significance levels are * - $p < 0.05$, ** - $p < 0.01$, *** - $p < 0.001$.

Base categories: Place of residence: Perm; Education: Higher; Visits per year: less then 1;

Time to purchase: in a week to play.

behavior are available which allows sellers to find or estimate consumers' willingness-to-pay.

First-degree price discrimination is a theoretical concept rather than a specific price strategy. In practice, sellers use strategies of personalized, tailored or conditioned pricing. These practices imply a similar idea, but are slightly different from each other by the way they are applied. 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 an imperfect form of first-degree price discrimination assumes charging consumers different prices, not necessarily their full reservation values.

Theatres provide a good context for price conditioning. First, about 50% of current purchases occur online, which allows the identification of consumers and the conditioning of the pricing strategy based on their purchasing history. Second, the theatre has already used a price discrimination strategy based on explicit consumer characteristics (second-degree price discrimination). Third, available individual-level data on purchases of a particular performance allow theatres to study their audience empirically and develop individual pricing strategies. Thus, real data on ticket purchases and survey data on hypothetical choice as well as socio-demographic characteristics give specific instruments for tailored pricing.

Class 1: Modest theatregoers. This class represents very frequent visitors who attend performances alone. These people are the most sensitive to price change and buy the cheapest tickets on average compared to other classes. They are consumers of popular culture, who enjoys ballet rather than opera, visit traditional productions and attend performancs at other theatres in Perm. Choosing a ticket, they mostly pay attention to price rather than quality of performance or seat. They choose seats in the circle or upper circle, which seems to be rational for a person with a low income. Among the less pronounced attributes this class includes people living in Perm region (these people constitute only 17% of respondents), unmarried people (41 percent) and those, who possess the lowest income (less than 14,000 rubles). Taking into account price sensitivity and eclectic tastes in performances we suggest the theatre management discount the prices on performances and seats when the house is not full. While modest customers mostly rely on price, they will respond to personal discounts. Their high frequency attendance suggests discounts based on the number of tickets purchased or a subscription system.

Class 2: Affluent customers. This is a wealthy type of theatregoer, who prefer new productions and performances conducted by Currentzis. The stalls are their most preferred seats. This class is the only one that purchases seats in the stalls. Members of this group demonstrate price insensitivity, consequently, they purchase the most expensive tickets on average compared to other consumers. This class unsurprisingly includes people with the highest income. We may conclude that when purchasing a ticket, these people make judgements about the performance and seat quality rather than by ticket price. We suggest the theatre management maintain a high level of ticket prices on the seats in the stalls. It is also in the interest of the theatre to make full-price tickets more valuable to visitors with a higher willingness-to-pay and to make discounts less valuable. A 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. This class also includes visitors, arriving from other cities, predominantly from Moscow and Saint-Petersburg. This fact permits to discriminate people outside Perm region by IP addresses.

Class 3: Old theatre friends. This is a loyal Perm resident, who does not visit other theatres in Perm, but actively visits the Perm Opera and Ballet Theatre and demonstrates a long purchasing history. They demonstrate higher sophistication compared to other classes, that is, they remember their past consumption and plan future visits to the theatre in advance. Members of this class have equal preference for opera and ballet and different conductors. However, they prefer to see the regular repertoire, and they are probably willing to wait for lower prices, when the play will move from the category of premiere to the category of regular ones. Their price sensitivity, moderate income and visits to regular plays allow them to save money in favor of frequent theatre visits. They prefer seats in the middle (tiered stalls and circle), that are considered the best in terms of value for money. Old theatre friends tend to purchase tickets early. The theatre can employ the strategy of dynamic pricing: reducing the price for seats in the middle of the house at the start and increase the prices on these seats as the house fills up. 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: Occasional theatregoers. This type of theatregoer attends the theatre rarely, but appreciates the quality of performances and seats. They enjoy expensive plays but visit not the most expensive seats in the house (seats in the middle of the house). They are insensitive to price change, but have less income compared to segments 2 and 3. Members of this group prefers opera to ballet, the regular plays than premiere ones, and equally value performances conducted by different conductors. As main goal of theatre attendance they point "to go out" and "to have fun". This describes them as rare visitors with high willingness-to-pay and the ability to perceive quality. One way to influence this type of consumers is to offer personal discounts on expensive and middle seats at expectedly less popular productions in order to increase their frequency of visits. Realizing that demand for seats in the tiered stalls and the circle is prefered mainly by people from classes 3 and 4, we suggest making discounts early (2-3 months before a play) for old theatre friends and increase the prices the month before the performance for occasional buyers and better attended performances.

7 Conclusion

The analysis of empirical studies devoted to the 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[1], in 2016 the Perm theatre covered only 17% of total expenses by revenue from ticket sales. The major part came from regional budget (75%) and the rest 8% was sponsorship.

In the performing arts market the issue of an effective pricing strategy is complicated by the specific characteristics of the product. Modelling the demand one should account for the combined structure of the 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. Theatrical productions are an experience good and a consumer's choice of performance in many respects depends on past consumption. In studies devoted to pricing strategies theatrical productions are considered to be perishable goods. This category describes products that cannot be inventoried and sold at a later time, here after a time of play. Theatre audiences are heterogeneous in terms of visit purpose, ability to perceive quality and willingness-to-pay.

It has been shown that price discrimination is an effective way to charge prices for perishable goods (Hetrakul & Cirillo, 2014). Considering heterogeneous theatre audiences, 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 for different theatre segments, allowing theatres to increase revenue from ticket sales.

The development of a price discrimination strategy requires data on consumer purchase history, and behavioral and socio-demographic characteristics. We employ data on online ticket purchases, which allows us to observe the consumer's name, email and history of attendance. We also collect experimental data on consumer choice in hypothetical situations. Experimental data permits us to induce variation in attributes insufficiently observed in real data. Questions on consumer's cultural participation and socio-demographic status allow us to describe consumer groups. The joint dataset with real and survey data combines the benefits and eliminates weak spots of each approach.

In order to identify consumer segments among theatre audiences we employ a class of discrete choice models (DCM) – the latent class model. LCM is a powerful tool to obtain insights into consumer segments and provide guidance to shape marketing policy. In effect, the model provides a clear picture of existing theatre audiences and marketing strategies that can be applied to different types of theatregoers. In this paper we generalize the LCM model for the case of partial

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

consumer data availability since some of consumer characteristics may be observed in one data source only. The LCM model divides visitors into modest, affluent, and occasional attendees and old theatre friends. Taking into account the price sensitivity of modest customers and their eclectic tastes we suggest the theatre management discount the prices on performances and seats when the house is not full. Realizing that this segment mostly relies on prices at the time of purchase, personal discounts for poorly attended performances and less popular seats will attract them. Since affluent attendees make up the only segment that purchases the seats in the stalls, we suggest the theatre maintain high prices for these seats. The average spent by these consumers may be increased by offering additional paid services. Since, old theatre friends are sensitive to price change and tend to purchase tickets early, it is rational to use 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 occasional customers differs by their consumption of qualitative productions and is less sensitive to price change. To increase revenue from this segment the theatre may introduce paid exclusive theatre events.

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

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Authors:

Evgeniy M. Ozhegov
National Research University Higher School of Economics (Perm, Russia).
Research Group for Applied Markets and Enterprises Studies. Research Fellow;
E-mail: tos600@gmail.com

Alina Ozhegova
National Research University Higher School of Economics (Perm, Russia).
Research Group for Applied Markets and Enterprises Studies. Young Research Fellow;
E-mail: arbuzanakova@hse.ru