The Influence of Other Alternatives on Consumer Choice*

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Abstract

In this paper, we test the existence of the direct influence of other available alternatives on the consumer's utility. By using the dataset from the specially designed experiment on individuals' choices of red wines we show that characteristics of other products in the choice set directly affect a consumer's utility of the product. We introduce choice set effects to the empirical demand model and show that it plays an important role in the widely used approach of employing rival products' characteristics as instruments to overcome the price endogeneity problem in demand estimation. The obtained results show that the exclusion condition is not satisfied for some of the rival products' characteristics, but is satisfied for other rival products' characteristics. The experimental design described in this paper can be used to improve the instrumental variables estimation of the choice models.

Keywords: Consumer Choice, Behavioural Bias, Endogeneity, IV
JEL codes: C25, C26, D12

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1 Introduction

The discrete choice models are a workhorse in empirical estimation of consumers' demand. These models were originally developed by McFadden (1976) and later were actively employed to estimate demand for differentiated products in both empirical IO (Berry, Levinsohn, and Pakes (1995), Nevo (2001), Petrin (2002), Berry and Haile (2014)) and marketing (Horsky, Misra, and Nelson (2006), Albuquerque and Bronnenberg (2009), Orhun (2009)). These models capture the interconnection of different brands available to consumers. When the consumer chooses the product, she also takes into account other alternatives available to her. In discrete choice models, the choice of the particular product depends on the utility of this product and the utilities of other products in the choice set.

However, standard models do not take into account that the characteristics of other products may directly affect utility. The utility of the product reflects the satisfaction level that the consumer expects to obtain by choosing the product. The utility level depends on other available products in the choice set. A consumer may get extra utility if the product is much better than other available products. This extra utility level depends on how good the other available alternatives in the choice set are. Suppose, the consumer chooses the wine. The same wine may provide lower utility in a choice set where other wines have better characteristics than in a choice set where other wines have less favorable characteristics. In this case, the characteristics of other available wines such as region or grape variety may directly affect the utility of the wine. In this paper, we show that characteristics of other products in the choice set directly enter consumer's utility of the product by using the dataset from a specially designed experiment on individuals' choices of red wines.

In the experiment, the participants were asked to provide their evaluations of each wine in their choice sets. We estimated whether the characteristics of other products in the choice set affect the subjective evaluation of the wine. To further consider the issue, we also estimated a multinomial logit model. We argue that the result obtained by using subjective evaluation of the product as a proxy for its utility is more robust to model misspecification than the discrete choice model estimation where only choices are observable.

Moreover, we show that the obtained results play an important role in the widely used approach of employing other products' characteristics as instruments for the market prices in demand function estimation. We provide evidence that some other products' characteristics directly enter a consumer's utility function and therefore the exclusion condition is not satisfied for them. If researchers use rival products' characteristics as an instrument for the prices and they directly affect consumer's utility, it leads to biased estimation of coefficients for prices.

Rival products' characteristics are widely used instruments to solve the price endogeneity problem caused by a potential positive correlation between the price and unobserved product's characteristics. More specifically, unobserved product's characteristics include quality. A monopoly or oligopoly firm with a high-quality product optimally raises the price to take advantage of consumers' appreciation of the product. Furthermore, to produce a high-quality product firms need to use high-quality inputs that are more expensive. These high production costs lead to the high product's price. The positive correlation between the price and the error term leads to the positive bias in the price coefficient estimates.

The rival products' characteristics can be considered as proper instruments if both relevance and exclusion conditions are satisfied. The relevance condition is satisfied if the endogenous variable and instrumental variable are correlated. This condition can be easily tested by regressing the market prices on rival products' characteristics and checking the F-statistic. The instrumental variable satisfies the exclusion condition if it is not correlated with the error term in the equation of interest. This condition requires the rival products' characteristics to affect the consumer's utility only through the prices but not directly. It is impossible to test whether the exclusion condition is satisfied by using market data because the market prices are correlated with the error terms. The true error term cannot be recovered because the true parameter values are unknown. We test whether the exclusion condition is satisfied for the characteristics of rival products by using a unique experimental design. First, prices are set randomly to eliminate their possible endogeneity problem. Second, in our experiment individuals are provided with random choice sets. The obtained results show that the exclusion condition is not satisfied for some of the rival products' characteristics, but is satisfied for other rival products' characteristics.

The influence of the other products' characteristics on consumer's choice that we consider in this paper has been described in several theories in behavioral economics. One of them is the model of context-dependent preferences proposed by Tversky and Simonson (1993) that considers the structure of choice set as a context. According to this model, people get extra value if the product is better in some aspects than other available products. This approach is close to the reference-dependent preferences model proposed by Kahneman and Tversky (1979), if we consider the characteristics of other available alternatives as a reference point. Sen (1997) argues that in the case of limited knowledge, the choice set itself provides information that the individual uses in her decision making. According to Sen, other alternatives affect the evaluation of the product by providing additional information about the quality of the product. For example, if the consumer observes that the new wine that she has not tried before is surrounded by well-known high-quality wines she may conclude that this new wine is also high-quality because the store manager combines the wines from the same range together. The choice set dependent preferences are reflected in such concepts as attraction and compromise effects with the support of the experimental evidence in Huber, Payne, and Puto (1982), Simonson and Tversky (1992). Chernev, Böckenholt, and Goodman (2015), Gao and Simonson (2016) study the influence of the choice set's size on purchase decision.

Our experimental design is different from those described in other papers. It allows us to eliminate individuals' heterogeneity and get robust results on the influence of other products' characteristics on an individual's utility of the product. Moreover, our discrete choice experiment is closer to the real-life environment as individuals were provided with pictures of real products along with the descriptions. Other alternatives and their characteristics may affect a consumer's utility through the different behavioral mechanisms described above. The purpose of this paper is not to distinguish them, but to show that at least one of them occurs in the consumer's evaluation of the product and its utility. This evidence is enough to question the validity of rival products' characteristics as instruments in demand estimation.

The obtained results show that there is a direct influence of other products' characteristics on the individual's utility of the wine, which varies across different demographic groups. Additionally, we tested how individual's wine drinking experience affects the role of the choice set effects responsible for the influence of other available alternatives and their characteristics on choices. We found that the choice set effects exist for both experienced and inexperienced individuals. Both groups react to other products' characteristics, but there are some differences in this reaction. Experienced individuals react to both the other wines' country of origin and grape variety, and inexperienced consumers react only to the country of origin.

This paper is organized as follows. In Section 2, we present the design of our experiment. In Section 3, we test whether other products' characteristics directly affect utility by using individuals' subjective evaluation. In Section 4, we introduce the model of the consumer's product choice and explain estimation procedures that we use. The results of the demand function estimations are presented in Section 5. Section 6 provides the robustness checks. In Section 7, we describe how the obtained results are related to the validity of rival products' characteristics as instruments for market prices. In Section 8, we conclude.

2 Experiment

2.1 Experimental design

In this paper, we use the dataset obtained from the discrete choice experiment described in Goryacheva and Nakata (2018). 1100 individuals of different age and gender participated in the survey in Japan. Firstly, they were asked about their demographic characteristics such as age, gender, household income, education, marital status and the number of adults (over 20 years) in the household. Then the individuals answered the questions about their red wine drinking experience: the age when they started drinking, the frequency of drinking, usual place to drink wine, reasons for purchasing wine, wines' characteristics that they take into account to make a choice. The individuals were asked about their preferences over red wines: favourite country-producer, grape variety, etc.

Each individual was provided with a choice set consisting of 5 wines. These 5 wines were randomly chosen for each individual from the list of 55 red wines prepared for the experiment. Each individual was provided with pictures of the bottles and labels of all wines from her choice set. After observing the information, the individuals were asked about their opinion of the wines ("What do you think about this wine?") For each wine they could choose one of six possible answers: "tasteless","a bit tasteless","neutral", "delicious", "very delicious" and "I do not know". After expressing their opinion about the wines' qualities, the individuals were asked about the factors that influenced their evaluations.

The feature of our experimental design is that most individuals were choosing among the wines that they have not tried before. As a result, they were in a situation where they had to figure out the quality of the product through its external characteristics and by using any other additional information that was available to them such as characteristics of other wines in their choice sets. To control for cases when the wine was familiar to the individual, we asked them whether they tried the wine before or know its market price.

At the next stage, the individuals were provided with the prices of the wines in their choice sets. These prices were randomly generated for each individual and individuals were aware of the randomness. Each individual had to choose one wine from the choice set or the outside option (none of them). After the choice was made each individual was asked about the wines characteristics that influenced her choice decision. Each individual was asked to make a choice three times. Each time the individual faced the same choice set with a new set of random prices.

Our experimental design allows us to have high variations in the product's characteristics and characteristics of other products that subjects face in a dataset. The variability occurs because individuals face different choice sets. The vector of other products' characteristics may be different for the same product in two different choice sets.

In our experiment individuals are provided with small choice sets consisting of 5 wines. This experimental design not only provides variability in products' characteristics that individuals face but also potentially reduces the effect of consideration set formation on the individuals' choices. That is, if the choice set is large, the individual may only make a decision based on a small subset of it, which is called in the literature a consideration set. For example, Fader and McAlister (1990), Roberts and Lattin (1991), Ben-Akiva and Boccara (1995) propose different models of consumer's consideration set formation. By restricting the choice set of the individuals to be small, we make it more likely that individuals will include all five wines into their consideration set.

It is important to note that our testing method is limited. It only tests for the violation of the exclusion restriction that may arise from the behavioral aspects of individuals' choices, i.e., characteristics of other available products affect the utility level of the individual. It does not test the validity of the supply side instruments, such as input prices.

2.2 Data

We use data on individuals' demographic characteristics, their wine drinking experience, characteristics of the wines, individuals' subjective evaluations of the wines and their choices from the experiment described above. Wines' characteristics observed by the individuals from the wines' labels include country of wine's origin, region, year, grape variety, and body of the wine. Table 1 presents descriptive statistics for the 55 red wines chosen for the experiment. 10 % of the wines are produced in Japan, and the rest of the wines are from foreign countries such as France, Chile, Italy, U.S.A. The wines in the dataset have different grape varieties and belong to different price categories.

The descriptive statistics for the characteristics related to the wine consumption behavior of the individuals are presented in Table 2. All individuals participated in the survey drink red wine, but they have different frequency of drinking: 64% of them drink red wine at least every month and 30% drink red

Table 1: Descriptive statistics of the wines

Country	Share(%)
Japan	10.9
France	27.3
Chile	14.5
Italy	20
U.S.A.	18.2
Other	9.1
Grape variety	
Cabernet Sauvignon	7.3
Pinot Noir	18.2
Merlot	14.5
Sangiovese	1.8
Cabernet Sauvignon+Merlot	27.3
Other	30.9
Price range (yen)	
<1500	16.4
1500 to 2500	25.4
2500 to 3500	29.1
3500 to 4500	20
>4500	9.1
Observations	55

wine at least every week. Many individuals choose Cabernet Sauvignon and Shiraz as favourite grape varieties. Most of the people (51%) are indifferent between red wines produced in Japan and those produced in a foreign country. People most often choose France as a favourite foreign wine producing country followed by Chile and Italy. Individuals mostly focus on the following wine's characteristics when they make a purchase decision: price (80%), country (49%), taste (41%), and region (32%).

We present the descriptive statistics for individuals' demographic characteristics in Table 3. The average age of participants is 52. The average starting age of drinking red wine is 26 years. In the dataset, we have individuals of both genders from different income groups and with different levels of education.

The individuals take into account different aspects of the wine when they evaluate the quality of the wine that they did not try before. In Table 4, we present the frequency of the criteria that affected individuals subjective evaluations of the wines. According to the results presented in Table 4, individuals relied most on the design of the bottle and its label in their wines' evaluations. Individuals also mentioned the country and the region of the wine as the factors that affect their evaluations.

In Table 5, we show characteristics of the wines that influenced individ-

Table 2: Wine consumption related characteristics

Average age of start drinking red wine	26.3
Average number of red wines usually at home	1.9
Items to focus on when purchasing a red wine	Share(%)
Country	49.4
Region	32.3
Producer's name	9.5
Certification	9.5
Year	6.4
Grape variety	18.9
Price	80.4
Design	10
Cork/ screw cap	5
Taste/color/smell	40.9
Expert's evaluation	2.9
Prises winner	4
Recommended	16.7
Reviews	3
Preferences for country of production	
Japan	22.7
Foreign countries	26.2
Indifferent	51.1
Favourite country, producer of the red wine	
France	34
Chile	24.8
Italy	24.6
Spain	15.7
U.S.A.	7.3
Australia	9.9
Other	4.5
Indifferent	47.4
Favourite grape variety	
Cabernet Sauvignon	19.6
Pinot Noir	11.4
Merlot	12.6
Shiraz	15.7
Sangiovese	5.1
Other	3.4
I don't know	3
The frequency of drinking red wine	
Almost every day	4.5
4-5 days a week	3.3
2-3 days a week	12.5
1 day a week	9.8
2-3 days a month	17.7
once a month	16.2
Once every 2-3 months	16.9
More rare	19
Observations	1100

uals' choices. Most of the people (66.6%) were influenced by the prices of the wines, 39% mentioned country of origin as a criterion that affected their choices among other criteria. Only 15% of the participants chose design as a factor that

Table 3: Demographic characteristics

Average age	51.7
Household income	Share(%)
< 2 million yen	9.8
2-4 million yen	21.5
4-6 million yen	23.8
6-8 million yen	19.8
8-10 million yen	11.4
≥ 10 million yen	13.6
Unmarried	24.1
Male	66.2
Education	
Middle school	1.2
High school	24.5
College	20.2
Bachelor	47.6
Postgraduate degree	6.4
Number of adults (over 20) in the household	
1 person	7.2
2 people	19.1
3 people	38.4
4 people	20.4
5 or more people	15
Observations	1100

Table 4: Criteria that affected subjective evaluations of the wines

	Share(%)
Shape and design of the bottle	48.1
The color and design of the front label	47.9
Font of the label	13.1
Details described on the front label	6.9
The color and design of the back label	3.8
Details described on the back lable	8.8
Producer	4.4
Name	6.8
Country and region	15.9
Grape variety	6.9
Tried the wine before	0.3
Observations	5500

influenced their decision even though the design was the most commonly chosen factor for the individuals' evaluations of the wine's quality. A potential explanation for this result is that individuals who assess the quality of the wines based on the label designs put a lower weight on quality and higher weight on the price when making a choice of which wine to buy. Individuals who care about quality when they make purchase choices look at characteristics other than label design for information on quality.

Table 5: Criteria that affected choices over wines

	Share(%)
Country	39.3
Region	22.8
Producer's name	6.2
Certification	5.8
Year	5.6
Grape variety	12.6
Price	66.6
Design	15.9
Cork/ screw cap	1.4
Taste/color/smell	11.2
None of the above	6.4
Observations	3300

3 Products' subjective evaluations

3.1 The influence of other products' characteristics on individual's subjective evaluation

In this section, we test whether the characteristics of other products directly enter consumer's utility function by using individuals' subjective evaluations. Even though there are many ways that alternative brands could affect the utility of buying a product, we consider the two effects which we think are most important. First, since individuals only have imperfect information on the actual quality of wines, they may use the comparison brands as signals. For example, consumers may consider any wine in a wine shop that has high-quality brands to be high-quality wine. However, in this case, we believe that it is reasonable to think that individuals to some extent understand the random nature of their choice sets in our experiment, and thus, do not consider the other brands to contain information on the product they assess. We believe that the comparison effect more likely affects their assessments. For example, a wine that is in a group with high-quality wines may be considered to be very low-quality, whereas when other brands are also low-quality consumers may not notice its low quality as much.

The purpose of this research is to show that consumers' utility of the wine is affected by the characteristics of its alternatives. We think that individuals' evaluations of the products in our experiment were affected by other products' characteristics more through the comparison effect than through the signaling effect because the individuals were aware that the wines in their choice sets were randomly chosen and they do not contain any information about the quality of each other. Overall, alternatives and their characteristics may affect consumer's perception of the product through the different behavioural mechanisms. As mentioned earlier, the purpose of this research is not to distinguish them, but to show that at least one of them affects consumer's evaluation of the product and its utility level.

We use individuals' subjective evaluations of the wines to test whether other products' characteristics directly affect consumers' preferences. We excluded individuals who answered "I do not know" to the question about wines' evaluations from our sample. To test the influence of other products' characteristics on individuals' subjective evaluations we run the following OLS regression:

$$S_{ij} = \kappa + X_j \pi + X'_{ij} \psi + \omega_{ij}, \quad (1)$$

where S_{ij} is individual i's subjective evaluation of product j, which is a discrete variable that varies from 1 (lowest evaluation) to 5 (highest evaluation), X_j is a vector of product j's characteristics, and ω_{ij} is an error term. $X_j = (X_j^1, X_j^2, ..., X_j^K)$, where X_j^k is a dummy variable that equals 1 if product j has characteristic k and 0 otherwise. $X'_{ij} = (X'^1_{ij}, X'^2_{ij}, ..., X'^K_{ij})$, where $X'^k_{ij} = \frac{1}{J-1} \sum_{l \neq j \in A_i} X_l^k$, and A_i is individual i's choice set.

We do not include wines' prices in Eq.(1) because, in our dataset, individuals evaluate wines before they observe any prices and use only information on products' characteristics. Our experimental design eliminates the connection between price and quality because the prices in an experiment are random and do not contain any information about the wine's quality.

The results of Eq.(1) estimation are presented in Table 6, Column 1. These results show that individuals' subjective evaluations of the wines' quality not only depend on the wine's own characteristics but also on some characteristics of other wines in the choice set. These results support our hypothesis that other products' characteristics directly enter the consumer's utility function.

3.2 Demographic groups

We want to test whether there are differences in reaction to other products' characteristics across different demographic groups. For this purpose, we use information on individuals demographic characteristics from our dataset that includes gender

Table 6: OLS regression and Rank regression

Variables	OLS	Rank regression
Own characteristics:		
Pinot Noir	0.0962***	0.0535
	(0.0362)	(0.0346)
Sangiovese	-0.447***	0.00510
	(0.0976)	(0.0932)
Cabernet Sauvignon	0.141***	-0.0182
	(0.0498)	(0.0475)
Cabernet+Merlot	0.0735**	0.0562*
	(0.0328)	(0.0313)
Japan	0.0744*	0.0532
	(0.0421)	(0.0402)
U.S.A.	-0.0989**	-0.0228
	(0.0387)	(0.0369)
Italy	-0.000983	0.0324
	(0.0377)	(0.0360)
France	0.161***	0.0724**
	(0.0344)	(0.0328)
Other products' characteristics:		
Pinot Noir	-0.0663	-0.0908
	(0.0742)	(0.0708)
Sangiovese	0.469**	0.679***
	(0.194)	(0.186)
Cabernet Sauvignon	0.282***	0.0662
	(0.101)	(0.0964)
Cabernet+Merlot	-0.0256	-0.000249
	(0.0660)	(0.0630)
Japan	0.0190	0.148*
	(0.0850)	(0.0811)
U.S.A.	0.0269	-0.0287
	(0.0772)	(0.0737)
Italy	-0.0232	0.0744
	(0.0775)	(0.0739)
France	0.00617	-0.0297
	(0.0697)	(0.0665)
Constant	3.374***	1.471***
	(0.0578)	(0.0552)
Observations	4,754	4,754
R-squared	0.029	0.011

and level of education. We created four subsamples: women with secondary education (high school and a junior college degree), women with higher education (bachelor and higher degree), men with secondary education, men with higher education.

We estimated an OLS regression with wines' subjective evaluations for

Table 7: OLS regression for different demographic groups

Variables	Female Secondary	Female Higher	Male Secondary	Male Higher
Own characteristics:				
Pinot Noir	0.0648	-0.102	-0.0195	0.228***
	(0.0737)	(0.0991)	(0.0794)	(0.0560)
Sangiovese	-0.778***	-0.418	-0.228	-0.407***
	(0.188)	(0.297)	(0.217)	(0.149)
Cabernet Sauvignon	0.183*	-0.000924	0.106	0.187**
	(0.107)	(0.143)	(0.104)	(0.0756)
Cabernet+Merlot	0.0550	-0.0829	0.00116	0.166***
	(0.0685)	(0.0980)	(0.0677)	(0.0502)
Japan	0.176**	-0.00675	0.117	0.0254
	(0.0876)	(0.116)	(0.0936)	(0.0636)
U.S.A.	0.108	-0.0827	-0.0192	-0.248***
	(0.0798)	(0.111)	(0.0797)	(0.0605)
Italy	0.200***	-0.111	-0.00146	-0.0746
	(0.0764)	(0.105)	(0.0797)	(0.0591)
France	0.259***	0.176*	0.162**	0.110**
	(0.0701)	(0.0973)	(0.0745)	(0.0526)
Other products' characteristics:				
Pinot Noir	-0.398***	-0.161	-0.400**	0.291**
	(0.146)	(0.200)	(0.167)	(0.118)
Sangiovese	-0.652*	1.275**	0.214	0.844***
	(0.395)	(0.602)	(0.422)	(0.297)
Cabernet Sauvignon	-0.0445	0.319	0.163	0.503***
	(0.215)	(0.287)	(0.220)	(0.152)
Cabernet+Merlot	-0.224*	-0.182	-0.0737	0.124
	(0.135)	(0.199)	(0.141)	(0.102)
Japan	0.0319	-0.181	0.0294	0.114
	(0.180)	(0.242)	(0.183)	(0.131)
U.S.A.	0.311**	-0.195	0.249	-0.128
	(0.157)	(0.220)	(0.165)	(0.121)
Italy	0.0930	-0.202	-0.0185	-0.0115
	(0.161)	(0.199)	(0.164)	(0.124)
France	-0.0981	0.180	-0.0284	0.0594
	(0.135)	(0.209)	(0.155)	(0.108)
Constant	3.452***	3.636***	3.379***	3.220***
	(0.114)	(0.151)	(0.127)	(0.0931)
Observations	1,077	589	1,083	2,005
R-squared	0.055	0.045	0.025	0.057

these four demographic groups. The obtained results are presented in Table 7. On average, women have higher subjective evaluations of the wines than men. For the wines' own characteristics, there are differences in reaction across these four groups, but all individuals tend to have higher subjective evaluations of wines produced in France. Most of the wines' own characteristics do not affect subjective evaluations of women with higher education and men with secondary education. Women with secondary education tend to have higher subjective evaluations of wine produced in Japan and Italy and men with higher education have lower evaluations of wine produced in the U.S.A. Regarding the grape varieties, women with secondary education and men with higher education have lower subjective evaluations of wine with a Sangiovese grape variety and higher subjective evaluations of wine with a Cabernet Sauvignon grape variety. Men with higher education give higher evaluations to wine with a Pinot Noir grape variety and the blended wines with Cabernet Sauvignon and Merlot grape varieties.

All four demographic groups react to other products' characteristics when they form the subjective evaluations of the wines but in a different way. Women with secondary education give higher evaluations to the wine if a greater number of other wines in the choice set were produced in the U.S.A. Women and men with secondary education give lower evaluations to the wine if a greater number of other wines have Pinot Noir grape variety. Women with higher education evaluate the wine lower if a greater number of other wines in the choice set have Sangiovese grape variety. The greater the number of other wines with Pinot Noir, Sangiovese or Cabernet Sauvignon grape varieties in the choice set is, the higher evaluation men with higher education give to the wine.

3.3 Heterogeneity of products' subjective evaluations

Results from the previous section show that the products' characteristics affect the individuals' subjective evaluations differently depending on gender and educational backgrounds. This indicates that individuals' heterogeneity matters in the formulation of subjective evaluations.

Results presented in Table 6, Column 1 potentially can be caused by the individuals' heterogeneity. The way of perceiving different characteristics of the products may vary across individuals. To capture the influence of other products' characteristics, we need to take into account the heterogeneity of consumers' preferences in our estimation. In order to test the robustness of obtained results, we want to check whether the influence of the characteristics of other available alternatives from the choice set on wines' subjective evaluations still occurs when we introduce individuals' heterogeneity.

One way to eliminate individuals' heterogeneity in subjective evaluations is to use a fixed effect model. The model assumes that there is an unobserved individual-specific component that affects her subjective evaluations of the wines. We can express this component as individual-specific constant κ_i in Eq.(1). This constant can be removed from the data by demeaning the products' characteristics in the choice set. However, we can not apply this approach to our regression. In Eq.(1) we include the characteristics of other products in the choice set as their mean in order to eliminate the order effect restrictions. Given this representation of other products' characteristics, estimation of the fixed effect model with both own and other products' characteristics leads to the multicollinearity problem.

For this reason, we use another approach to eliminate the individual-specific fixed effect. We transfer individuals' subjective evaluations of the wines into wines' ranks. For example, individual i has the choice set of the wines $A_i = \{a, b, c, d, e\}$ and her subjective evaluations of these wines are $S_{ia} = 5, S_{ib} = 2, S_{ic} = 2, S_{id} = 4, S_{ie} = 1$. We assign the following ranks to these wines according to their subjective evaluations: $R_{ia} = 4, R_{ib} = 2, R_{ic} = 2, R_{id} = 3, R_{ie} = 1$. The higher rank corresponds to the higher subjective evaluation of the wine in the choice set.

We run the same regression as in Eq.(1), but we substitute subjective evaluations with the derived ranks of the wines:

$$R_{ij} = \kappa + X_j \pi + X'_{ij} \psi + \omega_{ij}. \quad (2)$$

The results of Eq.(2) estimation are presented in Table 1, Column 2. Many of the wine's own and other wines' characteristics that were significant in the subjective evaluations regression become insignificant in the rank regression. For example, both the wine under consideration and other wines being Cabernet Sauvignon positively and significantly increased the subjective evaluation of the wine under consideration in the regression, but both are insignificant in the rank regression. This indicates the strong fixed effects, which are positively correlated with own or other wines being Cabernet Sauvignon. One interpretation is: individuals are happy to see Cabernet Sauvignons in their choice set, thus, they give higher subjective evaluations to all of the wines, regardless of whether they are Cabernet Sauvignons or not. That is why the relative rankings do not change significantly. Some other wines' characteristics such as Sangiovese grape variety and Japan as a country of origin affect the individual's utility level. The obtained results show that even if we eliminate individuals' heterogeneity, some of the other wines' characteristics directly affect an individual's utility of the wine.

4 Consumers' demand model

4.1 Logit model

Next, we use data on choices to test whether the characteristics of other products affect the utility of a product. To do so, we estimate the logit choice model with the following specification. There are N consumers, J products, and T trials. Consumer i's indirect utility function of buying product j in trial t is:

$$u_{ijt} = \beta_0 + \beta_1 p_{ijt} + X_j\alpha + X'_{ij}\gamma + \xi_j + \eta_{ijt}, \tag{3}$$

where p_{ijt} is the price of product j for consumer i in trial t, X_j is a vector of product j's characteristics, X'_{ij} is a vector of characteristics of the products from the choice set of consumer i excluding product j, ξ_j is the mean (across consumers) of product j's unobserved characteristics, η_{ijt} is the idiosyncratic utility shock.

The coefficients in the consumer's utility function reflect her attitude toward the different products' characteristics. Each individual had to make a choice 3 times, each time she faced the same choice set, but the prices of the wines were different. For this reason, there is a subscript t for the prices, but not for the products' characteristics in the consumer's utility function.

We consider a logit demand function. Each consumer faces a choice set consisting of several products and an outside option. In our model, we consider a general case, where the consumer has her own choice set. The consumer chooses the option that gives her the highest utility. We assume that the utility shock for each choice η_{ijt} is i.i.d. extreme value distributed. In this case, the probability of choosing product j by consumer i who faces the choice set A_i in trial t has the following closed form expression:

$$Pr(y_{it} = j) = \frac{\exp(\delta_{ijt})}{\sum_{l \in A_i} \exp(\delta_{ilt})}, \tag{4}$$

where

$$\delta_{ijt} = \beta_0 + \beta_1 p_{ijt} + X_j\alpha + X'_{ij}\gamma + \xi_j. \tag{5}$$

The mean utility of the outside option (not to buy any product) is normalized to zero ($\delta_0 \equiv 0$).

4.2 MLE

The main identification assumption is that for any product j unobserved product's characteristics ξ are mean independent of the observed product characteristics X.

In our dataset, unobserved product characteristics ξ are independent of other products' characteristics because individuals' were provided with random choice sets. Formally:

$$E[\xi_j|X, X^{'}] = 0.$$

To estimate coefficients of the demand function we use the maximum likelihood estimator. We do not face the price endogeneity problem, and there is no need to use instruments because individuals were provided with random prices and they were aware of it.

The likelihood function is:

$$L(\theta) = \prod_{t=1}^{T}\prod_{i=1}^{N} Pr(y_{it}),$$

$$Pr(y_{it} = j) = \frac{\exp(\delta_{ijt}(\theta))}{\sum_{l\in A_i}\exp(\delta_{ilt}(\theta))},$$

where $\theta = (\beta_0, \beta_1, \alpha, \gamma)$ is a vector of parameters, and A_i is consumer i's choice set consisting of J products. $\alpha = (\alpha_1, \alpha_2, ..., \alpha_K)$, $\gamma = (\gamma_1, \gamma_2, ..., \gamma_K)$, $X_j = (X_j^1, X_j^2, ..., X_j^K)$, where X_j^k is a dummy variable that equals 1 if product j has characteristic k and 0 otherwise. $X_{ij}^{'} = (X_{ij}^{'1}, X_{ij}^{'2}, ..., X_{ij}^{'K})$, where $X_{ij}^{'k} = \frac{1}{J-1}\sum_{l\neq j\in A_i} X_l^k$.

The log-likelihood function is:

$$\ln L(\theta) = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\sum_{j\in A_i} I(y_{it} = j)\delta_{ijt}(\theta) - \log(\sum_{l\in A_i}\exp(\delta_{ilt}(\theta)))\right), \qquad (6)$$

where $I(\cdot)$ is an indicator function. We maximize the log-likelihood function and get the parameter estimates:

$$\hat{\theta} = \arg\max_{\theta}[\ln L(\theta)].$$

5 Results

The results of the estimation for the logit demand model are presented in Table 8, Column 1. The estimated coefficient for the variable that represents the share of other wines with Cabernet Sauvignon grape variety in the choice set is positive, which means the higher the share of Cabernet Sauvignon wines in the consumer's choice set, the higher the utility that individual gets from this particular wine. If the wine itself contains a Cabernet Sauvignon grape variety, it provides higher utility to the consumer in comparison with wines containing other grape varieties. We observe the same results for the blended wines containing Cabernet Sauvignon and Merlot grape varieties. The coefficients for both variables representing wine's own and other wines blends are positive and significant. The wine containing the Sangiovese grape variety on average gives lower utility to the individual than wines containing other grape varieties. There is no effect of the share of other wines with Sangiovese grape variety in the choice set on an individual's utility as the estimated coefficient is not significant. If we consider the estimated coefficients for dummy variables that represent different grape varieties, Cabernet Sauvignon wines on average give the highest utility to individuals, followed by Pinot Noir wines and blended wines with Cabernet Sauvignon and Merlot grape varieties.

The country of origin also affects the consumer's utility level. Wine produced in Japan gives higher utility to the consumer in comparison with the wines produced in other countries. At the same time, the greater number of other wines in the individual's choice set are produced in Japan, the higher utility level the individual gets from the particular wine. The wine would give higher utility if other wines from the individual's choice set were also produced in Japan. The wines produced in the U.S.A. provide lower utility to individuals than wines produced in other countries. The share of other wines produced in the U.S.A. in the choice set does not affect an individual's utility level. The estimated coefficients for Italy and France dummy variables are positive and significant: the wines produced in Italy or France on average provide higher utility to the individuals than wines produced in other countries. The greater the number of other wines produced in Italy in the individual's choice set the higher is the utility level that the individual gets.

The obtained results show that on average the individual's utility level depends not only on wine's own characteristics but also on characteristics of other wines in her choice set. These results are consistent with the results obtained for individuals' subjective evaluations of the wines.

6 Robustness checks

6.1 Exogeneity of the other products' characteristics

To get unbiased estimated coefficients other products' characteristics X' must be uncorrelated with the error term that includes unobserved product's characteristics ξ. The estimated coefficient for the characteristic k of other products in the choice set in Eq.(5) is:

$$\hat{\gamma}_k = \gamma_k + \frac{cov(X'^k, \xi)}{var(X'^k)},$$

Table 8: Demand function estimation

Variables	Choice Inside	Choice Outside
Own characteristics:		
Pinot Noir	0.394***	0.295***
	(0.0906)	(0.0702)
Sangiovese	-1.218***	-1.237***
	(0.3268)	(0.2766)
Cabernet Sauvignon	0.498***	0.300***
	(0.1298)	(0.0975)
Cabernet+Merlot	0.207***	0.0956
	(0.0827)	(0.0698)
Japan	0.68***	0.394***
	(0.1032)	(0.0802)
U.S.A.	-0.318***	-0.221***
	(0.0964)	(0.0761)
Italy	0.336***	0.134
	(0.0969)	(0.0776)
France	0.249***	0.2549***
	(0.0815)	(0.0664)
Log(Price)	-1.465***	-1.467***
	(0.0420)	(0.0427)
Other wines' characteristics:		
Pinot Noir	0.115	-0.013
	(0.0689)	(0.0573)
Sangiovese	0.0182	-0.154
	(0.1923)	(0.1396)
Cabernet Sauvignon	0.246***	0.0771
	(0.1034)	(0.0793)
Cabernet+Merlot	0.141***	-0.0229
	(0.0641)	(0.0536)
Japan	0.352***	0.0923
	(0.0792)	(0.0686)
U.S.A.	-0.118	0.0237
	(0.0781)	(0.0602)
Italy	0.252***	-0.0082
	(0.0753)	(0.0576)
France	-0.0031	0.055
	(0.0669)	(0.0510)
Constant	10.595***	11.161***
	(0.3971)	(0.3686)
Observations	3300	3300
LLF	-5169.7	-5183.3

where γ_k is the true coefficient.

If $cov(X'^k, \xi) \neq 0$, the estimated coefficient $\hat{\gamma_k}$ is biased. To test whether unobserved product characteristics are correlated with other products' characteristics we use the following procedure. We estimate the same demand model as we did above, but we substitute the characteristics of other products in the individual's choice set with the characteristics of the randomly chosen products outside of the individual's choice set. Instead of Eq.(5), we obtain the following expression for the mean level of utility:

$$\delta_{ijt} = \beta_0 + \beta_1 p_{ijt} + X_j \alpha + X''_{ij} \gamma' + \xi_j, \qquad (7)$$

where X''_{ij} is a vector of characteristics of the products outside of the consumer i's choice set. Characteristics of other products outside of the individuals' choice sets cannot affect their utility levels and their choices respectively. For this reason $\gamma'_k = 0$.

The estimated coefficient for the characteristic k of other products outside of the choice set in Eq.(7) is:

$$\hat{\gamma}'_k = \gamma'_k + \frac{cov(X''^k, \xi)}{var(X''^k)} = \frac{cov(X''^k, \xi)}{var(X''^k)}.$$

If estimated coefficient $\hat{\gamma}'_k = 0$, then we can conclude that $cov(X''^k, \xi) = 0$ and there is no endogeneity problem of other products' characteristics.

The results of Eq.(7) estimations are presented in Table 8, Column 2. The estimated coefficients for all characteristics of the randomly chosen wines outside of the individuals' choice sets are not significant. The estimated coefficients for the shares of wines with Cabernet Sauvignon grape variety and blended wines with Cabernet Sauvignon and Merlot grape varieties are significant when we consider other wines in the individuals' choice sets and they become insignificant if we consider other wines outside of the individuals' choice sets. We observe the same results for the coefficients of the variables that represent the shares of other wines produced in Japan and Italy: coefficients are significant for the wines in individuals' choice sets and insignificant for the wines outside of the individuals' choice sets. According to these results, characteristics of other products are uncorrelated with the unobserved product characteristics. For this reason, we obtain unbiased estimated coefficients of the characteristics of other products in Eq.(5).

6.2 Experience and individuals' reaction

There is a possibility that the behavioral mechanisms responsible for the influence of other available alternatives and their characteristics on choices can play an important role for the inexperienced and a negligible role for experienced consumers. For example, List (2004) shows that the influence of the endowment effect on consumers' decision-making process gets smaller as their market experience increases.

To test whether wine drinking experience affects individuals' reaction to

Table 9: Demand function estimation for experienced and inexperienced individuals

Variables	Inexperienced Individuals	Experienced Individuals
Own characteristics:		
Pinot Noir	0.4058***	0.4206***
	(0.1019)	(0.1808)
Sangiovese	-1.3584***	-1.1272***
	(0.4881)	(0.4787)
Cabernet Sauvignon	0.5039***	0.5294***
	(0.1572)	(0.2571)
Cabernet+Merlot	0.2299***	0.1859
	(0.0983)	(0.1684)
Japan	0.6466***	0.8272***
	(0.1229)	(0.2204)
U.S.A.	-0.1523***	-0.6962***
	(0.1129)	(0.1807)
Italy	0.5129***	-0.0512
	(0.1134)	(0.2016)
France	0.3642***	-0.0798
	(0.0981)	(0.1677)
Log(Price)	-1.507***	-1.3914***
	(0.0519)	(0.0801)
Other wines' characteristics:		
Pinot Noir other	-0.0099	1.6503***
	(0.3132)	(0.6069)
Sangiovese other	1.0437	-1.8559
	(1.0204)	(1.3671)
Cabernet Sauvignon other	0.7689	1.6254***
	(0.4918)	(0.8389)
Cabernet+Merlot other	0.2281	1.3132***
	(0.2971)	(0.5483)
Japan other	1.0264***	2.5311***
	(0.3793)	(0.7368)
U.S.A. other	-0.1586	-1.1726***
	(0.3599)	(0.5629)
Italy other	1.0887***	0.7609
	(0.3539)	(0.6713)
France other	0.2592	-0.9263
	(0.3118)	(0.5516)
Constant	10.7814***	10.4402***
	(0.4713)	(0.7697)
Observations	2304	996

other products' characteristics, we divided all individuals into two groups. The first group includes people who drink red wine at least one day a week. People who drink red wine less often were combined in the second group. We use the frequency of wine drinking as a proxy for wine drinking experience, assuming that people who drink wine more often know more about red wines and their characteristics. We estimated the same logit model as in Section 4 for these two groups of individuals. The results of this estimation are presented in Table 9.

According to the obtained results, experienced and inexperienced consumers have a similar reaction to wine's own characteristics, except for dummy variables that represent blended wines with Cabernet Sauvignon and Merlot grape varieties and wines produced in Italy and France. The estimated coefficients for these dummy variables are not significant for experienced individuals.

The results show that both groups react to other products' characteristics, but they do it in a different way. The grape varieties of other wines affect utility functions of experienced individuals but do not affect the utility functions of inexperienced individuals. The inexperienced individuals react to other wines that were produced in Japan and Italy, and experienced individuals react to the other wines produced in Japan and U.S.A. Inexperienced individuals are more sensitive to the wine's price than experienced individuals.

7 Instrument validity of rival products' characteristics

7.1 Price endogeneity problem

In this section, we describe how obtained results are related to the validity of the commonly used approach when characteristics of rival products are used as instruments to overcome the endogeneity problem of market prices. In the demand function, we have aggregate demand or consumers' choices as the dependent variable and market price as the explanatory variable to estimate consumers' reaction to different price levels. Typically, when we use a simple OLS for estimation, the resulting price coefficient estimates are often insignificant, or even significantly positive, implying an upward-sloping demand curve. The reason for this is the potential positive correlation between the market prices and unobserved products' characteristics.

When the firm sets the price for its product, it takes into account product's characteristics including those that are unobserved by the econometrician ξ. For example, ξ can be considered as the quality of the product, then ξ and p are correlated because high-quality products tend to have high costs and high prices respectively. Another way is to consider ξ as a variable that denotes average consumers' value for all unobserved characteristics of the product. In case of wine choice, ξ may include reputation, the design of the bottle and label of the wine. Individuals may perceive these unobserved characteristics differently, that is why we consider ξ_j as a product-specific mean to highlight the heterogeneity of the consumers' reaction to the different products' attributes. When the firm chooses the price of its product, it takes into account consumers' reaction to all product characteristics including those that are unobserved by the econometrician. Firms, usually, conduct marketing research to learn how consumers react to different characteristics of the products and choose the price level respectively. This correlation between prices and unobserved product characteristics create a price endogeneity problem that leads to biased coefficient estimates for the price in the consumers' demand function.

There are several approaches to solve the price endogeneity problem in the estimation of the discrete choice models. The first approach is to include product-specific dummy variables to control for unobserved product characteristics. This method is applicable for micro-datasets with a small number of brands as it requires additional parameters to be estimated. If the number of brands is too large, there might not be enough observations to estimate product-specific constants.

The second approach involves the use of instrumental variables for the market prices. The most popular instruments are costs' shifters (input prices) or characteristics of rival products. In this paper, we consider validity of rival products' characteristics. 2SLS and GMM instrumental variables estimators require linear relationships between outcome and dependent variables, which introduces some limitations for the non-linear discrete choice models. To get a linear relationship Berry (1994) propose an inversion technique to find the implied mean levels of utility for each product. Berry, Levinsohn, and Pakes (1995) use this method for market-level data to estimate demand and supply functions in the U.S. automobile industry. They use the method of moments estimator with characteristics of rival products as instruments. Later this approach was extended by combining market-level data with consumer-level data in Petrin (2002), Berry, Levinsohn, and Pakes (2004), Goolsbee and Petrin (2004). Control function approach allows using instrumental variables to overcome the endogeneity problem for non-linear models. Petrin and Train (2010) apply the control function approach for solving the price endogeneity problem of households' choices among television options.

Many papers try to find the best instruments for the BLP model. Reynaert and Verboven (2014) using Monte Carlo simulations show that optimal instruments proposed in Chamberlain (1987) reduce small sample bias and increase the estimator's efficiency and stability. However, these optimal instruments depend in a specific way on the product's own characteristics and the characteristics of the other products, which still requires inclusion and exclusion conditions to be satisfied. The validity of rival products' characteristics as price instruments was questioned in Armstrong (2016). He shows that the dependence of prices on other products' characteristics through markups disappears in large markets and estimators based on these IV are consistent with a large number of small markets and inconsistent in a large market setting. His critique is related to the inclusion condition, while we are arguing that the exclusion condition is not satisfied for these instruments in some cases.

7.2 Bias in estimates of price coefficient

Below we show the consequences of using characteristics of rival products as instruments for the market prices in discrete choice models if the exclusion condition is not satisfied.

First, we consider the case of the 2SLS estimators for market level data. Suppose, there are J products, I consumers and M markets. The utility of consumer i from product j in market m is:

$$u_{ijm} = \beta_0 + \beta_1 p_{jm} + X_{jm}\alpha + \xi_{jm} + v_{ijm}, \tag{8}$$

where p_{jm} is price of product j in market m, X_{jm} is a row vector of observed characteristics of product j, ξ_{jm} is unobserved part of product j's characteristics, v_{ijm} is an idiosyncratic taste shock.

In the standard model under the assumption that consumers have multinomial logit demand function the share of product j in market m is:

$$s_{jm}(\theta) = \frac{exp(\delta_{jm})}{\sum_{l=0}^{J_m} exp(\delta_{lm})},$$

where $\delta_{jm} = \beta_0 + \beta_1 p_{jm} + X_{jm}\alpha + \xi_{jm}$ is the mean level of utility for product j, $l = 0$ is an outside option (not to buy any product) with $\delta_{0m} = 0, \forall m$, $\theta = (\beta_0, \beta_1, \alpha)$ is a vector of the parameters.

By using the inversion method proposed by Berry (1994) we get a vector of mean utilities for all products in market m:

$$\delta_m(\theta) = s^{-1}(s_m, \theta),$$

where s_m is a vector of observed market shares of the products. Once we obtained mean utilities from the market shares we can estimate the following linear regression:

$$\delta_{jm} = \beta_0 + \beta_1 p_{jm} + X_{jm}\alpha + \xi_{jm}. \tag{9}$$

Suppose we estimate the coefficients of this regression by 2SLS estimator and the characteristics of other products are used as instruments for the market prices.

In the first stage market prices are regressed on the characteristics of other products:

$$p_{jm} = \tau_0 + X'_{jm}\mu + \eta_{jm}, \tag{10}$$

where X'_{jm} is a row vector of the other products' characteristics for product j in market m.

The predicted market prices $\hat{p}_{jm} = \hat{\tau}_0 + X'_{jm}\hat{\mu}$ are obtained from the first stage. Then the market prices are substituted with the predicted values $\hat{p}$ in Eq.(9):

$$\delta_{jm} = \beta_0 + \beta_1\hat{p}_{jm} + X_{jm}\alpha + \xi_{jm}. \tag{11}$$

As we showed above in this paper, the characteristics of other products may directly enter the consumer's utility function. In this case, they become part of the error term in Eq.(8):

$$v_{ijm} = X'_{jm}\gamma + \epsilon_{ijm}.$$

In this case, the true mean utility of product j in market m is:

$$\delta_{jm} = \beta_0 + \beta_1 p_{jm} + X_{jm}\alpha + \xi_{jm} + X'_{jm}\gamma. \tag{12}$$

As a result, when we estimate Eq.(11) we get a biased price coefficient:

$$\hat{\beta}_1 = \beta_1 + \frac{cov(\hat{p}, X'\gamma)}{var(\hat{p})} = \beta_1 + \frac{cov(X'\hat{\mu}, X'\gamma)}{var(X'\hat{\mu})}.$$

The estimated coefficient is biased because $cov(X'\hat{\mu}, X'\gamma) \neq 0$.

Suppose now we have microdata on individuals' choices of the products instead of market level data. The mean utility of product j for consumer i is:

$$\delta_{ijm} = \beta_0 + \beta_1 p_{jm} + X_{jm}\alpha + \xi_{jm}. \tag{13}$$

In order to estimate coefficients of the demand function and overcome the price endogeneity problem, we use a control function approach with characteristics of other wines as instruments. We need to use the control function approach because we cannot apply inversion to get a linear expression as we do not observe products' shares.

In the control function approach we estimate the same regression as we did in the first stage of 2SLS (Eq.(10)) for the market level data, but now we are interested in residuals instead of predicted prices. We insert these obtained residuals $\hat{\eta}_j$ into Eq.(13) to control for unobserved product characteristics. Even if we control for other unobserved factors, characteristics of rival firms in the error term are correlated with the market prices that leads to the biased estimated coefficient of the price.

Our results in the previous sections of the paper, show that there is a behavioral component in consumers' choices that captures the direct influence of other products' characteristics on utility level. We show that some other products' characteristics cannot be used as instruments for the market prices as this will lead to the biased estimated coefficient of the price. This bias appears because the exclusion condition is not satisfied for these instruments.

7.3 Simulation

We use simulation to see the size of the bias of the price coefficient if we use other products' characteristics that enter the utility function directly as instruments for the market prices.

We assume there are 1100 markets. Each market has five wine brands competing with each other. These five wine brands are randomly chosen for each market from the list of wine brands that was used in the experiment. To generate mean indirect utilities of the consumers we use estimated coefficients presented in Table 8, Column 1. We generate unobserved products' characteristics $\xi \sim U(0,1)$ that enter consumers' utilities functions. We derive the wines' prices for each market as equilibria of Bertrand oligopoly competition under the assumption of a multinomial logit demand function of the consumers. The generated prices of the wines are positively correlated with unobserved products' characteristics. Next, we calculate the market shares of the wine brands for each market.

First, we estimate the coefficients of the indirect utility function without any correction for the price endogeneity problem by using generated data. For this purpose we use GMM to estimate the following equation of interest:

$$\ln(s_{jm}) - \ln(s_{0m}) = \beta_0 + \beta_1 p_{jm} + X_{jm}\alpha, \tag{14}$$

where s_{jm} is a market share of product j in market m, s_{0m} is a market share of the outside option in market m. Second, we estimate Eq.(14) by IV GMM estimator, where we use other products' characteristics as price instruments.

The obtained results are presented in Table 10. The first column represents the true values of the indirect utility function coefficients that we use for the data generating process. The second column shows the coefficients from GMM

Table 10: Demand function estimations for simulated data

Variables	True Coefficients	Baseline Estimation	IV Estimation
Own characteristics:			
Pinot Noir	0.394	0.2478***	1.1698***
		(0.0285)	(0.0809)
Sangiovese	-1.218	-0.6620***	-2.4718***
		(0.0990)	(0.1585)
Cabernet Sauvignon	0.498	0.4244***	0.7380***
		(0.0408)	(0.1017)
Cabernet+Merlot	0.207	0.2359***	0.4130***
		(0.0259)	(0.0563)
Japan	0.68	0.6059***	1.5916***
		(0.0346)	(0.0946)
U.S.A.	-0.318	-0.1131***	0.6784***
		(0.0322)	(0.0827)
Italy	0.336	0.3704***	1.2236***
		(0.0308)	(0.0865)
France	0.249	0.1271***	1.1475***
		(0.0263)	(0.0834)
Log(Price)	-1.465	-0.4708***	-5.3140***
		(0.0351)	(0.3123)
Constant	2.595	3.4503***	8.3079***
		(0.0408)	(0.3164)
Observations		5500	5500

estimation without any correction for the price endogeneity. In this case, the estimated price coefficient is upward biased because of the positive correlation between prices and unobserved products' characteristics. The last column represents the results from the IV GMM estimator when we use other products' characteristics as price instruments. The estimated price coefficient is heavily downward biased. This bias occurs because the exclusion condition is not satisfied for other products' characteristics.

Next, we want to see how big is the influence of the biases in the estimated price coefficients on price elasticities. Using β_1 from demand function estimation the own-price elasticity of product j in market m is:

$$E^d_{jm} = \frac{\partial s_{jm}}{\partial p_{jm}} \frac{p_{jm}}{s_{jm}} = \beta_1(1 - s_{jm}).$$

Table 11 shows calculated own-price elasticities of demand for the wines in one of the markets for both estimations with and without correction for the price endogeneity. The bias of the estimated price coefficient incurred by using other products' characteristics as instruments when the exclusion condition is not

Table 11: Own-price elasticities of demand

	True Elasticity	Baseline Estimation	IV Estimation
Wine 1	-1.1562	-0.3716	-4.1939
Wine 2	-1.0739	-0.3451	-3.8954
Wine 3	-1.2304	-0.3954	-4.4629
Wine 4	-1.1638	-0.3740	-4.2216
Wine 5	-1.2759	-0.4100	-4.6281

satisfied leads to the inaccurate predictions of the price elasticities.

8 Conclusion

In this paper, we test the existence of the direct influence of other available products and their characteristics on the consumer's utility. For our analysis, we use a dataset on individuals' choices and their subjective evaluations of the red wines obtained from the experiment. To provide evidence of the presence of the behavioral component in the consumer's decision-making process we estimated whether the characteristics of other products in the choice set affect the individual's subjective evaluation of the wine.

We also estimate the consumer's choice model with characteristics of other products from the choice set in consumer's utility function. We introduce this modification in our model to reflect a behavioral aspect of the consumers' decision-making process. This behavioural aspect can be described as choice set dependent preferences: when the consumer chooses the product, her satisfaction level from the particular product depends on other available alternatives in her choice set and their characteristics. We argue that the result obtained by using subjective evaluation of the product as a proxy for its utility is more robust to model misspecification than the discrete choice model estimation where only choices are observable.

The obtained results provide evidence that other products' characteristics directly affect the consumer's utility level. We found that the behavioral component exists for both experienced and inexperienced individuals. Both groups react to other products' characteristics, but there are some differences in their reaction. Experienced individuals react to both other wines' country of origin and grape variety, and inexperienced consumers react only to the country of origin.

The obtained results are important for solving the price endogeneity problem in demand function estimation. We show that the exclusion condition may not be satisfied for some of the rival products' characteristics as they directly enter the consumer's utility function. In this case, rival products' characteristics cannot be used as instruments for the market prices to overcome the endogeneity problem.

Our experimental design allows for testing of the exclusion condition for instrumental variables. The experimental design described in this paper can be adopted for instrumental variable estimation of choice models. If there is a need for using instruments to solve the endogeneity problem the exclusion condition of an instrumental variable can be tested by running a similar experiment with the randomness of the endogenous variable and choice sets of the individuals.

References

Albuquerque, P., and B. J. Bronnenberg (2009): "Estimating demand heterogeneity using aggregated data: An application to the frozen pizza category," *Marketing Science*, 28(2), 356–372.

Armstrong, T. B. (2016): "Large market asymptotics for differentiated product demand estimators with economic models of supply," *Econometrica*, 84(5), 1961–1980.

Ben-Akiva, M., and B. Boccara (1995): "Discrete choice models with latent choice sets," *International Journal of Research in Marketing*, 12(1), 9–24.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile prices in market equilibrium," *Econometrica: Journal of the Econometric Society*, pp. 841–890.

——— (2004): "Differentiated products demand systems from a combination of micro and macro data: The new car market," *Journal of Political Economy*, 112(1), 68–105.

Berry, S. T. (1994): "Estimating discrete-choice models of product differentiation," *The RAND Journal of Economics*, pp. 242–262.

Berry, S. T., and P. A. Haile (2014): "Identification in differentiated products markets using market level data," *Econometrica*, 82(5), 1749–1797.

Chamberlain, G. (1987): "Asymptotic efficiency in estimation with conditional moment restrictions," *Journal of Econometrics*, 34(3), 305–334.

Chernev, A., U. Böckenholt, and J. Goodman (2015): "Choice overload: A conceptual review and meta-analysis," *Journal of Consumer Psychology*, 25(2), 333–358.

Fader, P. S., and L. McAlister (1990): "An elimination by aspects model of consumer response to promotion calibrated on UPC scanner data," *Journal of Marketing Research*, pp. 322–332.

Gao, L., and I. Simonson (2016): "The positive effect of assortment size on purchase likelihood: The moderating influence of decision order," *Journal of Consumer Psychology*, 26(4), 542–549.

Goolsbee, A., and A. Petrin (2004): "The consumer gains from direct broadcast satellites and the competition with cable TV," *Econometrica*, 72(2), 351–381.

Goryacheva, E., and K. Nakata (2018): "Demand estimation with the quality's subjective evaluations," Working paper.

Horsky, D., S. Misra, and P. Nelson (2006): "Observed and unobserved preference heterogeneity in brand-choice models," *Marketing Science*, 25(4), 322–335.

Huber, J., J. W. Payne, and C. Puto (1982): "Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis," *Journal of Consumer Research*, 9(1), 90–98.

Kahneman, D., and A. Tversky (1979): "Prospect theory: An analysis of decision under risk," *Econometrica*, 47(2), 263–291.

List, J. A. (2004): "Neoclassical theory versus prospect theory: Evidence from the marketplace," *Econometrica*, 72(2), 615–625.

McFadden, D. (1976): "The revealed preferences of a government bureaucracy: Empirical evidence," *The Bell Journal of Economics*, pp. 55–72.

Nevo, A. (2001): "Measuring market power in the ready-to-eat cereal industry," *Econometrica*, 69(2), 307–342.

Orhun, A. Y. (2009): "Optimal product line design when consumers exhibit choice set-dependent preferences," *Marketing Science*, 28(5), 868–886.

Petrin, A. (2002): "Quantifying the benefits of new products: The case of the minivan," *Journal of Political Economy*, 110(4), 705–729.

Petrin, A., and K. Train (2010): "A control function approach to endogeneity in consumer choice models," *Journal of Marketing Research*, 47(1), 3–13.

Reynaert, M., and F. Verboven (2014): "Improving the performance of random coefficients demand models: the role of optimal instruments," *Journal of Econometrics*, 179(1), 83–98.

Roberts, J. H., and J. M. Lattin (1991): "Development and testing of a model of consideration set composition.," *Journal of Marketing Research*.

Sen, A. (1997): "Maximization and the act of choice," *Econometrica: Journal of the Econometric Society*, pp. 745–779.

Simonson, I., and A. Tversky (1992): "Choice in context: Tradeoff contrast and extremeness aversion," *Journal of Marketing Research*, 29(3), 281.