(Dynamic) Willingness to pay and e-commerce: Insights from sparkling wine sector in Russia

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Abstract

Although economic theory clearly provides reasons for a hedonic price function to change over time, this is not how it is traditionally approached empirically. For wine, which is one of the most widely used implications of hedonic price analysis, such time invariance can be traced down to the issues of data availability and price rigidity in the food and beverage sector. The development of e-commerce changes both these premises, providing reasons for more frequent price adjustments and making price data available at each point of time. Is willingness to pay for particular product attributes indeed time-invariant? In this paper, daily price quotes from the largest online grocery market in Russia are used to address this question using sparkling wines as an example. The results indicate that time invariance might be a rather strong empirical assumption, suggesting that the time dimension should be included into hedonic price studies whenever the data allows for it.

Keywords

consumer valuation; hedonic price function; e-commerce; dynamic willingness to pay

1. Introduction

A hedonic price function explains the price of a product as a combination of implicit prices of its attributes. Such an approach does not explicitly assume the attribute prices to be time-invariant: Pakes (2003) argues that hedonic function changes over time due to shifts in the manufacturer's cost expectations or consumer preferences shifts. Yet implicit prices are generally modelled as constant in empirical studies and deviation from this self-imposed assumption might call forth doubts regarding the general applicability of hedonic price analysis (see e.g. Faye and Le Fur, 2019). Is willingness to pay for a particular product attribute time-invariant? While research studying factors that affect consumers' willingness to pay (WTP) for a certain product attributes as well as time variation of prices through a prism of seasons, holidays, sales or socio-demographic and macro factors is abundant (e.g. Oczkowski and Doucouliagos, 2015; Capitello et al., 2015), the question whether (and how) the willingness to pay for particular attribute changes over the time often remains neglected.

The majority of hedonic price analyses use cross-sectional data to assess WTP. The few exceptions that exploit both cross-sectional and time dimension of the data still quantify a single coefficient per attribute for the whole time period (Benfratello et al., 2009; Bombrun and Sumner, 2003; Brentari et al., 2015; Cross et al., 2011). Such a skewed distribution towards static hedonic models that focus on a basket of products with prices measured at a certain point of time (or average prices over a few periods) might be driven by various reasons, including limited data availability and price rigidity. While some authors use data that are issued and updated unfrequently (e.g. wine catalogues or wine guides as in Angulo et al., 2000; Oczkowski, 1994; Haeger and Storchmann, 2006), others might argue that the product characteristics do not change over time (Griliches, 1971) and grocery prices are extremely rigid, rendering collecting data of higher frequency useless. Price stickiness has been a prominent feature of grocery markets: food prices may remain unchanged for many weeks or months, sometimes even years (Herrmann et al., 2005; Fassnacht et al., 2012; Loy and Schaper, 2014). The rapid development of online retailing is expected to bring more flexibility in prices by reducing costs of price adjustments (Biswas, 2004; Brynjolfsson and Smith, 2000). This prediction of the information economics has already been validated in recent large-scale high-frequency and predominantly non-food studies (Gorodnichenko et al., 2014; Lünnemann and Wintr, 2011; Gorodnichenko and Talavera, 2017). For the grocery sector, the evidence is still scarce, although Cavallo (2018) provides first insights into the market by showing that the active expansion of the internet tech giants such as Amazon in the food sector contributes positively to its dynamics. An increased price flexibility and availability of higher frequency price data call forth the WTP studies to accommodate these new challenges and opportunities. Yet almost no research that would explicitly consider dynamic aspects of consumer valuation seems to be readily available. This study aims at filling this gap using online sparkling wine prices in Russia as an example.

Of roughly 100 thousand studies on hedonic price analysis referenced in Google Scholar, almost 15 thousand entries include wine in their title or abstract. Even if these numbers overestimate the true picture (for instance, Lockshin and Corsi, 2012, include considerably lower number of studies to their review analysis), the interest to the subject does not seem to fade away as over 10% of all the hedonic wine studies are from 2018-19. By now it is well-documented that vintage (Angulo et al., 2000; Bombrun and Sumner, 2003), region (Landon and Smith, 1998), appellation of origin (Bazoche et al., 2013; Cross et al., 2011), grape variety (Boatto et al., 2011; Oczkowski, 1994), wine style (Schamel and Anderson, 2003), expert opinion (Cacchiarelli et al., 2015; Caldas and Rebelo, 2013), awards (Schamel, 2003), as well as packaging and labeling (Barber et al., 2006; Mueller et al., 2010) are important factors that contribute to the wine price formation.

Much less is known about sparkling wine, which is a dynamically evolving sector (Wilson, 2018). The precious little information that exists can be summarized as follows. In line with the broader wine-related literature, sensory and non-sensory attributes of sparkling wines affect consumers' preferences, with information about production process affecting expectations while not impacting informed liking (Vecchio et al. 2019). Demand for Champagne is inelastic since it is usually perceived as a luxury product which to a large extent is bought on special occasions (Bentzen and Smith, 2008). Prosecco consumers in Italy are price sensitive (Onofri et al., 2015), and perceive it as a product of 'medium-high' positioning, which is more appealing for households that opt for a higher unit price (Dal Bianco et al., 2018). Whether Prosecco enjoys any special reputation outside Italy is less clear (see e.g. Dal Bianco et al., 2018; Trestini et al., 2018). Consumers typically perform poorly in blind tastings but show significant preferences for Champagne when labels are shown (Lange et al., 2002). Consumers buying at large-scale retailers are willing to pay a higher price premium for quality signals than those buying in specialized shops, since the latter can reduce information asymmetry by sharing quality information (Boatto et al., 2011). Not surprisingly, most of the empirical evidence available comes from European countries and the US. Following the recent consumption trends, an increasing body of analysis focuses on emerging economies, especially China (Yu et al., 2009; Capitello et al., 2015; Cardebat and Jiao, 2018; Hu and Baldin, 2018). Russia, on the other hand, has rarely been in the focus of WTP studies, including for wine-related products (Galati et al., 2017 is an exception), possibly due to the country's wide-spread image as a spirits or beer-drinking nation as opposed to 'classic' wine-drinking countries. It will be later demonstrated that this view of the Russian drinking patterns is only partially correct, with sparkling wines playing a prominent role in Russian consumption.

Which role do particular sparkling wine attributes play in generating sparkling wine prices in Russia? Does WTP for particular features change over time? These questions are addressed in the empirical example that builds on prices for sparkling wine collected in the largest Russian online grocery market around Christmas time. Sparkling wines are especially associated with holidays with popping campaign corks being an integral part of welcoming a new year: The monthly value of sparkling wine sales in Russia increases three- to four-fold as the end of the year approaches (Statista, 2019).

Using various marketing channels plays a particularly important role in addressing consumers in emerging countries (Wine Intelligence, 2012) and if predictions of the economics of information theory are correct, maturing online markets – increasingly important to the younger consumers – should add flexibility to prices by significantly reducing price adjustment and search costs (Bakos, 1997). If true, the online channel might make prices less rigid and introduce dynamics to price premia for individual attributes over time - an issue that has not been addressed in the scientific discussion so far.

The remainder of the paper is structured as follows. The following section provides a brief introduction to the Russian market, including its alcohol consumption mix, regulations and the development of the sparkling wine sector in recent years. The next section briefly recapitulates the basics of a hedonic price model and summarizes challenges related to its empirical implementation. Finally, the data used in the empirical part is introduced and results are reported and discussed. The results show that estimated parameters from individual daily models vary significantly around the panel coefficients with most deviations occurring for the product attributes with the highest WTP shortly before or during the Christmas and New Year holidays. These outcomes expand the earlier findings suggesting that integrating time-dimension in hedonic analysis should no longer be neglected if one wants to understand how price dynamics work.

2. The Russian market

Although rarely considered a wine-drinking country, Russia is nevertheless one of the world's largest consumers of sparkling wine: in 2016, 2.4 Mhl of sparkling wine were consumed in the country (Karlsson, 2016). In per-country terms it is outperformed solely by Germany, but also in per-capita terms Russia belongs to the world leaders in sparkling wine consumption. Starting as a mostly spirits-drinking nation after the breakdown of the USSR, Russia successively moved to split its consumption evenly between beer and spirits, reducing the total amount of consumed alcohol from over 10 liters (of pure alcohol) in 2000s to 7.6 liters in 2016. Although the proportion of wine in alcohol consumption is still small, it has been increasing over time, especially in 2010s. In 2016, per-capita wine consumption was at 1.08 liters of pure alcohol, and its share in consumption mix reached 14%, roughly about a sixth of it - sparkling wines.

Around 10 % of the world sparkling wines are produced in Russia, which is also a major importer of the product. Not surprisingly, imports are sensitive to the development of the Russian economy: Between 2014 and 2016, the years of low oil prices and the deepening recession, 70% of wines that were consumed in Russia were also produced within the country (MWBI, 2019). As the economy revives, wine imports increase, fueled by growing interest of the younger consumers (Jenkins, 2018). Imports of sparkling wines in terms of volume grew steadily in the last few decades (more than ten-fold between 2000 and 2018), only interrupted by the periods of economic downturn. Imports in terms of value are more volatile, suggesting switching between qualities of sparkling wine depending on the internal demand. On the average, imports get more expensive over time, which is not surprising since the Russian consumers tend to put more trust in products of foreign origin and associate high price with high quality (Yang et al., 2019) for which the Russian consumers show an increased willingness to pay for wine compared to mid-2010s (Jenkins, 2018).

As sparkling wine consumers in the country get younger, internet as a distribution channel plays an increasing role in reaching consumers. With a population of 114 million people and internet penetration of about 80%, Russia belongs to the largest retailing markets in Europe. The projected size of Russia's e-commerce market is over 52 billion USD by 2023. According to Morgan Stanley, more than half of the Russians buy online at least once a month (Henni, 2018), a proportion that is expected to go up the moment the regulations on sales of alcohol are relaxed (Khrennikov, 2018). As of now, the online market that is otherwise booming in Russia, does not officially exist for alcoholic beverages, sparkling wine included. Internet sales are illegal and even if an online retailer show-cases the products on the online shop, the logistic behind the purchase often includes going to a physical store to collect the reserved product. While the legalization of internet sales that was expected on January 1, 2019, is still pending (MWBI, 2019), the online channels are increasingly used as a way to inform and attract consumers, also in the wine sector. A case in point is Invisible and WineStyles that use youth-oriented slang and graphics to attract younger generation or build extensive online wine catalogues (Moiseenko, 2017).

Over two-thirds of online-initiated sales in the country take place in Moscow (another 20 % are sold in Saint Petersburg, the second largest city). The buyers are young and mostly female: In 2017, 52 percent of the buyers were women aged 21-31, who are not necessarily the end consumers themselves, rather personal assistants or secretaries of business executives (Komonov, 2018). Corporate clients, especially in the energy, construction or finance sectors, that spend heavily on wine for the purpose of holiday gifting for their employees and business partners are the most desirable targets for wine distributors who seek to "secure important seasonal sales during the New Year period", which is unsurprising given that 30 to 50% of fine wines are sold during this time of the year (Moiseenko, 2017).

3. Theory and empirics

3.1. Hedonic price function

Hedonic price analysis has been intensively used to quantify the influence of various product characteristics on its price since the pioneering work of Waugh (1928). Here, theoretical hedonic price function is introduced only briefly while empirical specification is discussed in more detail in the following sub-section. Hedonic price function is derived from the utility (U) maximization problem of a consumer who chooses a unit of wine represented by a vector of attributes (Z) subject to a certain budget constraint (Y):

$$Z = (z_1, z_2, \dots z_n) \tag{1}$$

$$Max\ U\ (Z, X) \tag{2}$$

$$Y = p(Z) + X \tag{3}$$

$$\frac{\frac{\delta U}{\delta z_j}}{\frac{\delta U}{\delta X}} = \frac{\delta p}{\delta z_j} = p_j \tag{4}$$

where X represents all the other commodities than wine and $p(Z)$ is the market price of Z. The marginal rate of substitution between the wine characteristics z_j and X is equal to implicit price p_j of the characteristics z_j, which can be represented by the coefficients of a price function for a wine i with a market price P_i:

$$Pi = a + \beta_1 z_{i1} + \beta_2 z_{i2} + \cdots + \beta_n z_{in} + \varepsilon \tag{5}$$

The market prices paid by the consumer equal to the sum of the marginal monetary values of the different product characteristics, reflecting consumer's valuation of the wine attributes (Rosen 1974).

3.2. Empirical specification

In the empirical part hedonic price function is estimated for the entire sample as well as for each individual day. The equation that is brought to the data for the daily estimations is

$$Price_i = a + \mathbf{B}\ Country_i + \mathbf{\Gamma}\ Grape_i + \mathbf{\Delta}\ Sugar_i + \mathbf{E}\ Type_i + \epsilon\ Champagne_i + \zeta Gift\ package_i + \eta\ Product\ Photo_i + \theta\ Origin_i + \vartheta Rating\ number_i + \kappa\ Average\ rating_i + \lambda\ Alcohol\ content_i + u_i \tag{6}$$

Where $Price_i$ is a price for the 0.75 liter bottle of a sparkling wine *i*, a is a constant; $\mathbf{B}, \mathbf{\Gamma}, \mathbf{\Delta}$ and $\mathbf{E}$ are vectors that include variables identifying the country of origin, grape composition, sugar content and grape type respectively; ϵ, ζ, η and θ are coefficients at the binary variables referring to a product being a Champagne[1], having a gift package or photo and a geographical designation. ϑ, κ, and λ refer to continuous variables describing the ratings (number of evaluations and their average value) and

[1] Since Champagne is perceived as a completely different product than sparkling wine by some consumers (I am grateful to the reviewers for pointing this out), the variable *Champagne* captures this effect, singling out the sparkling wine produced in the Champagne region under specific rules from sparkling wines produced under rules of appellation in general (*Origin*).

alcohol content in %. Table 1 provides an overview of individual categorical variables in the model and respective reference groups in each category.

Table 1. Variable description

Variable	Description
Country	Armenia, Chile, France, Italy, Russia*, Spain
Grape	Single grape, Cuvée, No information available*
Sugar	Dry*, Semi-dry, Semi-sweet, Sweet
Type	White*, Rosé, Red
Champagne	Yes, No*
Gift package	Yes, No*
Product photo	Yes, No*
Origin	Yes, No*

* indicates the reference category.

The respective attribute gets the value of 1 when the product information on the web-page mentions it and equals 0 otherwise. If a certain attribute is not mentioned on the product page, e.g. appellation of origin for Champagne, it is not assumed that the consumer should be aware of such information anyway, but rather the data is collected and coded as is, with 1 for *Champagne* and 0 for *Origin*. In the sample there are three Champagnes that did not have an explicit mentioning of an appellation and they received 0 in the Origin variable. A robustness check that assumed the opposite - that all consumers associate Champagne with a controlled appellation and coding Origin with 1 for all Champagnes - does not change coefficients much.

The panel specification adds the time dimension t and the time fixed effects μ_t, that account for the factors that might affect all the sparkling wine prices in the same way over time (e.g. income factors or exchange rates):

$$Price_{it} = a + \mathbf{B}\, Country_i + \mathbf{\Gamma}\, Grape_i + \mathbf{\Delta}\, Sugar_i + \mathbf{E}\, Type_i + \epsilon\, Champagne_i + \zeta Gift\, package_i + \eta\, Product\ Photo_i + \theta\, Origin_i + \vartheta Rating\ number_i + \kappa\, Average\ rating_i + \lambda\, Alcohol\ content_i + \mu_t + u_{it} \quad (7)$$

In order to make sure that most bottlenecks that are sometimes discussed in relation to hedonic price analysis (e.g. wrong functional form, multicollinearity) are avoided, in the empirical part these critical issues are addressed. For instance, the specification test (the Box-Cox transformation) suggested that both linear and log-linear forms can be applied to represent the data. The log-linear estimates are reported in the results part since recent literature tends to favor this specification. The overall conclusions, however, hold in the linear specification as well. The results from a log-log model are very close to reported results too given that there are only a few metric variables that can be taken a logarithm of in the model. To deal with possible multicollinearity, the correlation coefficients between all the variables are calculated: the highest observed value is between attributes “sweet” and “alcohol content” (<0.66), suggesting no multicollinearity problem in the data. Finally, since the analysis builds on the information provided on the web-portal, the objective characteristics available to the consumers via labels – not subjective quality – are in the focus of this study. According to Boatto et al. (2011), signals appearing on the labels have a more relevant positive effect on wine prices than the brand reputation, and consumers are more willing to pay a higher price premium for such quality signals in a large-scale retail environment as compared to a specialized niche shop.

All the estimations are conducted using E-views 10. In the results part the panel estimates are reported in detail while daily estimates (77 models, one for each day of the sample) are summarized in the graphical form. On the diagrams the daily price effect estimates from individual daily cross-sectional models are depicted as points on the time line jointly with their 90 and 99% confidence intervals. Additionally, the panel estimate is plotted as a line that does not change over time to facilitate the comparison of the results. To arrive at price effect in percent as reported in the diagrams the method by Halvorsen and Palmquist (1980) was used, in which the price effect is calculated as $(e^{\beta} - 1)x100$, where β is a respective estimated coefficient from a log-linear model. The monetary price effects are calculated at the average sample price (887.87 rubles). The following section provides more details on the data that is used in the empirical part.

4. Data

The data was collected on the web-portal Utkonos.ru, the country’s largest online grocery retailer that has been operating in Russia since 2000. Since 2011, Utkonos operates as a pure online platform, which is visited daily by about 24-30 thousand users (hupso.com, 2019; whoismark.com, 2019). The assortment of Utkonos.ru covers almost 40 000 products and more than nine million consumers already made their grocery purchases in the shop (Utkonos.ru). The platform operates 24/7 without holidays and offers a 2-hour delivery interval, a possibility to get the order on the same day as well as reject either a part of or the whole order without paying its cost and delivery in case of a doubt regarding the quality of the products. Although the online supermarket only delivers in the city of Moscow and the Moscow region, this is where 75% of online alcohol sales of the entire country take place (Komonov, 2018). Utkonos was the third largest Russian internet platform by the sales volume in the mid-2010s (Forbes, 2013). Even if today it only ranks 15th (Henni, 2019), Utkonos.ru is the only grocery retailer on the list of 40 largest e-commerce platforms and the largest online grocery retailer in the country, which was a decisive criterion for the purpose of data collection: While there are more specialized wine retailers in the country (see e.g. Moiseenko, 2015, for an overview), there seem to be no more important online players on the market.

The price quotes for sparkling wines were collected over 77 days – from December 1, 2017, to February 15, 2018. The data collection ended on the day when Utkonos removed all its alcohol products from the online shop in mid-February in a – belated – compliance with state regulations on marketing and sale of alcohol beverages online (Decree 612 On Approval of the Rules for Sale of Goods by Remote Means was signed in 2007). All the information that was available on the portal was used as product attributes. These attributes are classical objective search characteristics that are available on the product web page. The summary statistics for categorical variables for the whole sample (the counts are the number of products with a particular attribute in the sample multiplied by the number of days the product was available at the online platform) are reported in Table 2.

Table 2. Summary statistics

		Frequency		Price (Ruble)				
		Count	Relative (%)	Mean	Median	Max	Min	Std. Dev
Country	Armenia	77	1	480	480	480	480	0
	Chile	57	1	1114	1270	1270	890	185
	France	835	11	2895	1380	8440	304	2370
	Italy	3854	49	740	629	2900	291	408
	Russia	2181	28	440	389	832	189	197
	Spain	924	12	768	676	1370	448	238
Champagne	Yes	348	4	5503	5820	8440	3399	968
	No	7580	96	676	560	2905	189	415
Gift package	Yes	1902	24	1804	932	8440	309	1853
	No	6026	76	599	519	2905	189	354
Product photo	Yes	7647	96	908	569	8440	189	1102
	No	281	4	341	329	449	265	83
Grape	Single grape	3817	48	701	660	1590	285	307
	Cuvée	3182	40	1243	630	8440	189	1609
	N. A.	929	12	438	344	1300	209	274
Origin	Yes	4644	59	921	676	8440	289	980
	No	3284	41	841	459	6590	189	1223
Sugar	Dry	3616	46	1134	759	8440	189	1339
	Semi-dry	663	8	1278	676	5900	232	1693
	Semi-sweet	2246	28	444	420	999	209	134
	Sweet	1376	17	788	699	1590	265	365
Type	White	5475	69	926	599	6390	189	1106
	Rosé	1825	23	922	639	8440	269	1182
	Red	628	8	457	399	670	265	132
Total sample		**7928**	**100**	**888**	**569**	**8440**	**189**	**1088**

Besides these attributes, information on alcohol content as well as number of ratings and their value was gathered. On the first day of the data collection there were 126 sparkling wines in the sample, of which Armenian (1), Chilean (2), French (17, of those 7 Champagnes), Italian (62), Russian (30) and Spanish (14). 73 sparkling wines have information about their protected geographic indication (origin) on the web page. The majority of sparkling wines were produced using a single grape variety (61), or a mixture of known varieties (cuvée, 52). For 13 products such information is missing. Most of sparkling wines in the sample are whites (85), followed by rosés (32) and reds (9) and are dry (58), followed by semi-sweet (32), sweet (25) and semi-dry (10). Most products have a photo (122) but no gift package (90). On the average, each sparkling wine has been rated about 5 times with an average rating of maximum available points.

As an observation count suggests, not all products were available throughout the entire sample period: The lowest number of sparkling wines available (86) was observed on January 10 and the missing observations make up about 18% of data. Overall, prices changed 263 times over the sample period. Only for 28 sparkling wines did prices remain the same throughout the 2.5 months. Assuming that the price of an unavailable product remained unchanged during its absence on the online portal, on the average, prices of 5 sparkling wines changed daily. On some days, however, up to 40 price changes could be observed simultaneously. This high dynamic of price changes around the holiday season might be the first indication of the time-varying nature of the WTP for certain product attributes, which will be tested empirically in the following section.

5. Results and discussion

First, a panel model with all the data is estimated in a log-linear form. The results are reported in Table 3. The estimated coefficients are shown along with their (robust) standard errors, p-values and a 90% confidence interval in panel A. Panel B reports price effects measured in % to the reference category and Panel C reports price effects in monetary terms calculated at the average sample price (887.87 rubles). Since the dependent variable is in logarithmic form, the lower and upper confidence intervals are no longer symmetric once reported in ruble or percentage form and the actual confidence interval is higher than 90%.

All time-varying price components that are similar for all products are absorbed by time fixed-effects in the reported model. The outcomes, however, are robust to model specification (pooled, random time or product effects - that are not shown here - or time fixed effects). The results discussed below are ceteris paribus, implying an effect of a variable when all the other parameters of the model are hold constant.

Table 3. Panel model results

	A. Panel estimate	Std. Err.	P-value	90% confidence interval Low	High	B. Price effect (%)	90% confidence interval Low	High	C. Price effect (Ruble)	90% confidence interval Low	High
C	4.81	0.02	0.00								
Armenia	0.09	0.01	0.00	0.08	0.10	9.31	7.91	10.72	82.63	70.20	95.21
Chile	0.43	0.02	0.00	0.40	0.47	54.42	48.44	60.65	483.20	430.07	538.46
France	0.55	0.02	0.00	0.52	0.59	74.06	68.09	80.23	657.53	604.56	712.38
Italy	0.42	0.02	0.00	0.38	0.45	51.59	46.68	56.66	458.01	414.42	503.07
Spain	0.36	0.01	0.00	0.34	0.38	43.06	40.56	45.59	382.28	360.14	404.81
Champagne	1.34	0.02	0.00	1.30	1.37	280.17	266.69	294.15	2487.57	2367.87	2611.68
Gift package	0.46	0.01	0.00	0.45	0.46	57.74	56.42	59.06	512.62	500.93	524.41
Product photo	0.54	0.02	0.00	0.51	0.57	71.85	67.32	76.50	637.91	597.72	679.19
Single grape	-0.07	0.01	0.00	-0.10	-0.05	-7.10	-9.18	-4.98	-63.06	-81.47	-44.24
Cuvée	0.07	0.01	0.00	0.06	0.08	6.76	5.68	7.85	60.01	50.40	69.72
Origin	0.12	0.01	0.00	0.10	0.14	12.48	10.51	14.48	110.79	93.32	128.58
Rating (N***)	-0.02	0.00	0.00	-0.02	-0.01	-1.56	-2.30	-0.78	-13.82	-20.41	-6.95
Rating (N eval.)	0.00	0.00	0.00	-0.01	0.00	-0.46	-0.53	-0.40	-4.12	-4.72	-3.53
Semi-dry	-0.03	0.01	0.00	-0.05	-0.02	-3.29	-4.58	-2.10	-29.17	-40.71	-18.61
Semi-sweet	-0.18	0.00	0.00	-0.19	-0.17	-16.55	-17.16	-15.94	-146.96	-152.37	-141.51
Sweet	0.14	0.01	0.00	0.12	0.15	14.61	12.80	16.45	129.72	113.66	146.04
Rosé	0.08	0.01	0.00	0.07	0.09	7.84	6.74	8.94	69.58	59.86	79.40
Red	-0.07	0.01	0.00	-0.08	-0.06	-6.97	-7.89	-6.05	-61.92	-70.02	-53.74
Alcohol content	0.07	0.00	0.00	0.07	0.07	7.25	7.01	7.49	64.35	62.21	66.49

Notes: Dependent variable: log(price). Robust standard errors reported. Full set of time fixed-effects included. Adjustments needed to calculate price effects in % calculated are made according Halvorsen and Palmquist (1980). The reference category for econometric estimation is Russian dry white sparkling wine with no product photo, gift package, or information regarding designated origin of the product. The monetary price effects are calculated at the average sample price (887.87 rubles). N=7701. Adjusted R-squared 0.74.

All the coefficients are highly statistically significant (at p<0.00), although their economic significance varies considerably between individual attributes. Figure 1 plots estimated effects in relative terms (%) next to each other clustered in three groups: large, moderate and minor effects. The price premia for non-binary variables (ratings and alcohol content) would slightly increase if adjusted by their standard deviations (the respective numbers would be roughly 8 for rating quantity, 0.8 for average number of stars in a rating and about 2 for the alcohol content, respectively) but remain low.

The largest price effect is related to the attribute 'Champagne', which is associated with a price premium of 280%. The country of production and advertisement-related attributes – gift package and product photo – also substantially affect willingness to pay. The availability of a photo on the product page is associated with a price premium of about 72%, and that of a gift package – of about 58%, compared to products that do not have these attributes.

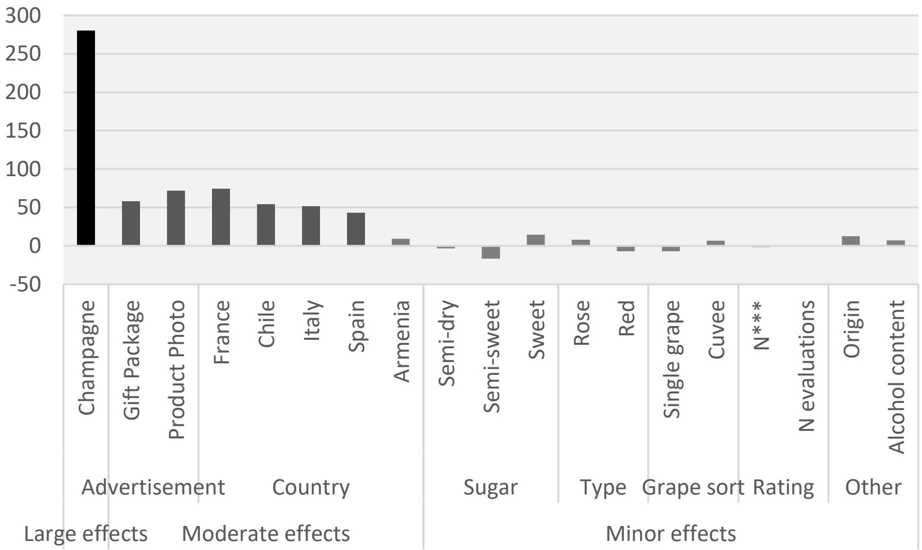

Figure 1. Price premiums (in %) from the panel model

Sparkling wines produced outside of Russia also enjoy a price premium, which varies between 9% for Armenia and 43-54 % for sparkling wines from Chile, Italy and Spain. The largest price effect is for France: over 74%, which is high, especially given that 'Champagne' is separated as an individual attribute.

Other attributes contribute rather little to price composition of sparkling wines, their economic significance is limited at best, even at the upper bounds of 90% confidence intervals. For the sugar content, sweet sparkling wines are valued higher than the dry ones (+15%), while semi-dry and especially semi-sweet wines are negatively discounted (about -3 and -17%, respectively). It seems that consumer value stronger sparkling wines (+7% per each additional unit of alcohol content), rosé wines

(+8%) over white and red styles (-7%), and cuvées (+7%) over products with no information on the grape sort used or sparkling wines made of a single grape (-7%).

These findings largely agree with existing studies (see e.g. Galati et al., 2017, for the country effect) and indicate that sparkling wines serve as New Year presents and that is why the region of production that approximates quality and reputation as well as gift package are of great significance. The result for a product photo further amplifies the importance of optics given that the ability to inspect the product is otherwise limited when shopping online. Ratings, on the other hand, do not seem to be taken seriously as quality signals. Other attributes, although significant in the panel, only to a minor degree affect price, which might be an indication that personal preferences and tastes might play a smaller role than the overall country reputation and optics in a situation when most of online consumers are personal assistants of business executives buying presents for third parties (Komonov, 2018).

In the following, the hedonic price function is estimated for each individual day of the sample and the results are summarized in the graphical form that plots the price effects (in %) for each product attribute over 77 days (Figures 2-7). Not surprisingly, the individual daily estimates revolve around the panel estimates, although the standard errors (as well as confidence intervals) are substantially larger, and respective p-values lower in the daily models. Given that the higher uncertainty in daily models is driven by a small(er) sample size and knowing that all the variables are highly statistically significant in the panel, let us proceed by looking at the development of price effects of major product attributes over time.

Most of the country[2] attributes follow the same pattern of the WTP increasing through the holiday season, beginning about a week before New Year's Eve and continuing almost up to the Old New Year (January 14), or at least to Christmas (January 7), shortly after which Russians return to work. The highest relative and absolute increase in the WTP is observed for France (Figure 2), with the price effect for the country attribute increasing by over 100 percentage points in comparison to the average or pre-holiday period. On the upper bound of the 90% confidence interval the increase is about four-five times higher. On the lower bound, the price effect is still positive.

[2] Chilean wine was sold out for large periods of the sample and the results are not discussed here in detail. It seems that prices go up during the holidays and go down a little thereafter, remaining higher than the 2017 values. WTP for Armenian wines remain low and mostly unchanged throughout the sample, which is not surprising since there is only one product of Armenian origin in the sample and its price has not changed over time.

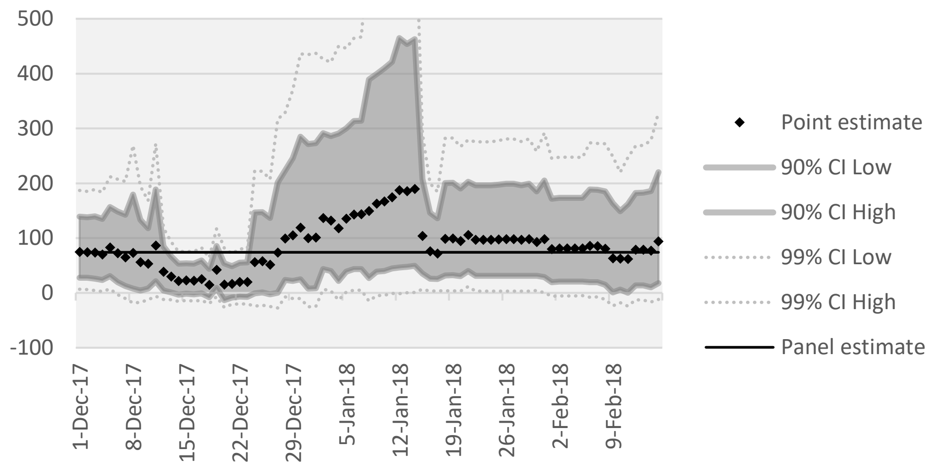

Figure 2. Price premium for the attribute "France" (in %)

Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – Russia.

Similar gradual increases can be seen for Italy (Figure 3) and Spain (Figure 4), although they are lower in their magnitude, in line with results of the panel model. These results might indicate that these sparkling wines might be bought as the holiday season evolves, not necessarily in advance, which seems to be the case for Champagne, which is stocked beforehand (Figure 5). Here the price premium already reaches its peak (460%) in mid-December and then drops by a half (to 140%) over the holiday times (which is caused by the most expensive Champagnes being sold out), and then reverts to the panel estimate (280%) after the festive season is over. Such a reverse to the mean is pronounced in most price attributes.

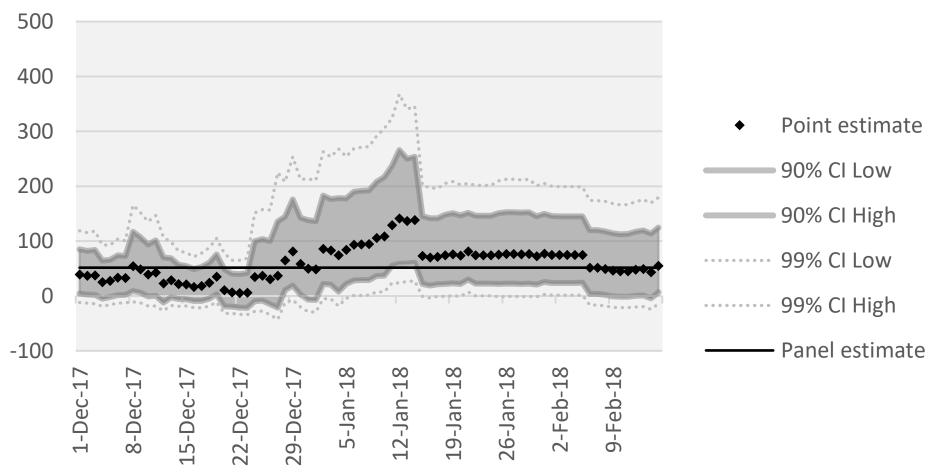

Figure 3. Price premium for the attribute "Italy" (in %)

Notes: See Figure 2.

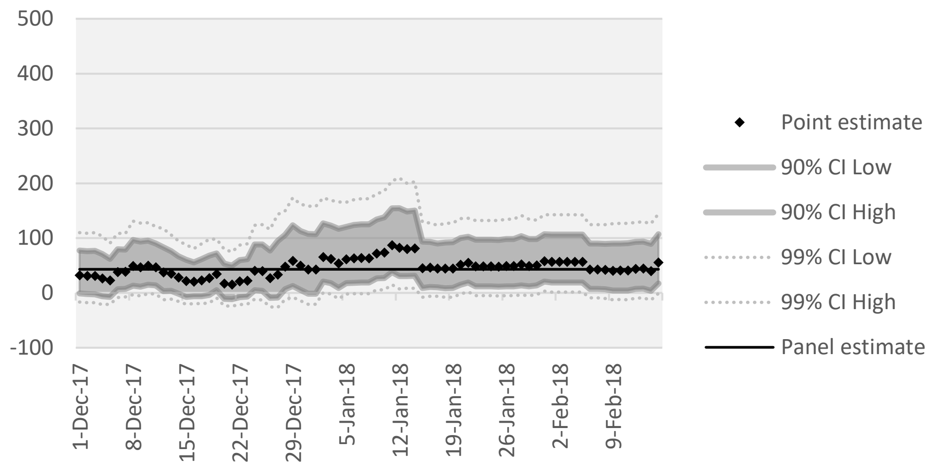

Figure 4. Price premium for the attribute “Spain” (in %)

Notes: See Figure 2.

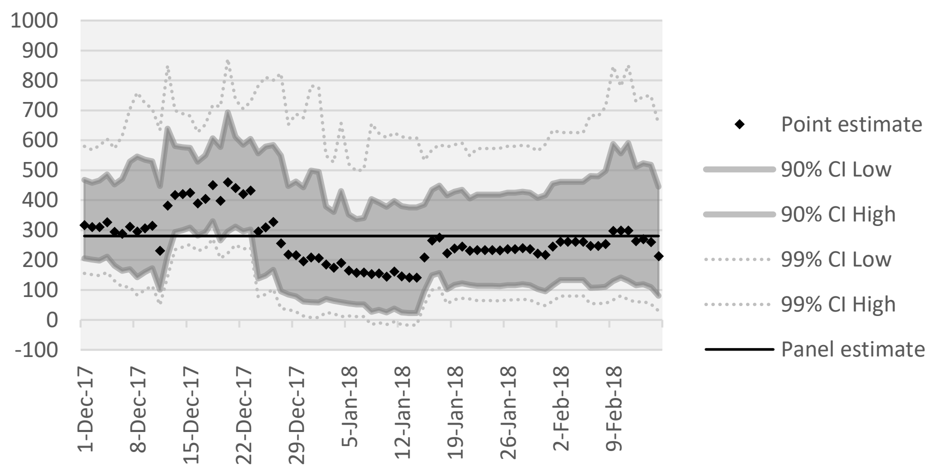

Figure 5. Price premium for the attribute “Champagne” (in %)

Notes: See Figure 2. Reference group – sparkling wines other than champagne.

Not surprisingly, WTP is high and increases for gift package (Figure 6) and product photo (Figure 7), with the latter skyrocketing right before New Year’s Eve and staying high up to the end of the holidays, then reversing and staying unchanged from the panel estimate for the rest of the sample. All these findings are in line with the assumption that sparkling wines are used as gifts, especially work-related, when the choice of the present is outsourced and the person making the choice is operating under existing knowledge of what good sparkling wine attributes are and the visual representation available on the web portal. Among the attributes with relatively lower WTP for attributes, fewer substantial changes are observed and the results are only shown in the appendix A.

6. Conclusion

While traditional hedonic price studies often rest on assumptions of price rigidity and limited access to the price data, online retailing changes them both, providing economic drivers for more dynamic price adjustments and making data available in each point of time. Such changes in the ground rules of the retailing raise the question whether hedonic price function is indeed as time-invariant as the majority of existing empirical studies suggests. The article provides first insights to the dynamic nature of hedonic prices and hence consumer valuation using daily price data on the sparkling wine sales in Russia around the Christmas time. Sparkling wine prices were collected at the largest online grocery shop in Russia, which is one of the major consumer markets for sparkling wines in the world. In Russia, sparkling wines are traditionally consumed and given as a present during the holiday seasons, with the weeks around New Year's Eve being the most celebrated holidays in the country.

The results suggest that objective attributes are highly relevant when choosing a product, and signals that appear on the label have a more relevant impact on the price than peer evaluations and ratings. While all the included product characteristics are highly statistically significant in the panel, some also possess high economic significance and remain statistically significant even when the estimation is repeated for individual days of the sample. The highest price premia are associated with imported sparkling wines (especially French ones, and Champagnes get an extra price premium), which are wrapped in a gift package and have a product photo on the web page. The rest of the attributes, including the sugar content, style or geographical appellation are far less important, economically, suggesting that in developing markets that may still lack the knowledge and experience, the country information that is reflected in higher prices is the most decisive factor in making a decision to buy.

The economically significant attributes are also the most affected by time: the premium for champagne goes up by about 180 percentage points as compared to the estimated sample average from the panel model. Similar shifts can be observed for all the economically significant variables. Even if these results are partially driven by the assortment composition on individual days (some products were missing from the sample on individual days), or are particular holiday-specific (the sample only covers two and a half months around New Year's Eve), they clearly indicate how misleading results from a single point-in-time snapshot studies may be and suggest that the time dimension needs to be incorporated to hedonic price analysis whenever data allows for it.

While these findings on dynamic consumer valuation are relevant for the retailers making assortment-related decisions throughout the year, it is important to keep in mind that these results come from a single market – Russia, which is even more narrowly defined by the data that was available for this study. The prices that are analyzed here come from a single – even if the country's largest – online grocery retailing platform that only operates in the capital region and are collected for a limited period of time. This all limits the possibility to extend these results to the entire country's population and makes it challenging to compare the results with outcomes from the other studies.

Despite these limitations, the analysis is an important step towards better understanding the complex dynamics of hedonic prices. As expected, estimates for product attributes do not stay constant, reacting to demand. They move, however, around their long-run estimates and return to those once the peak season has passed. While a recent study pointed to high volatility of hedonic price estimates that seem to undergo structural and cyclical changes over time and concluded that estimations of consumer willingness to pay, both short and long term, are more or less useless, this paper argues that these findings are consistent with theory and that the changing nature of hedonic estimates implies that we need more research on the willingness to pay to better explain these fluctuations, not less. More frequent and detailed price data from online retailing might be useful in achieving this goal.

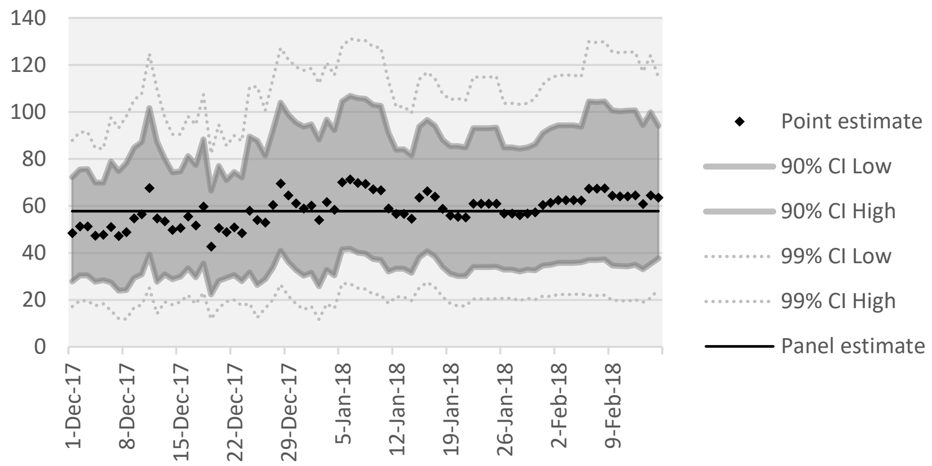

Figure 6. Price premium for the attribute "Gift package" (in %)

Notes: See Figure 2. Reference group – products without a gift package.

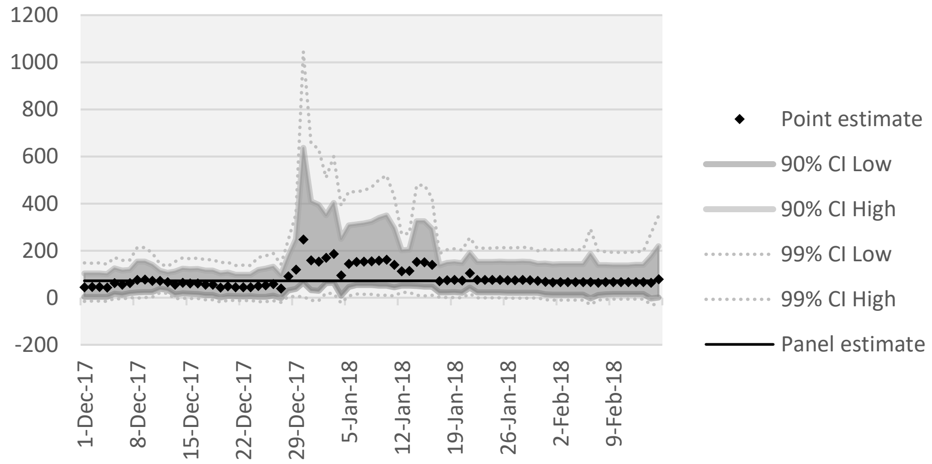

Figure 7. Price premium for the attribute "Product photo" (in %)

Notes: See Figure 2. Reference group – products that do not have a photo on the product page.

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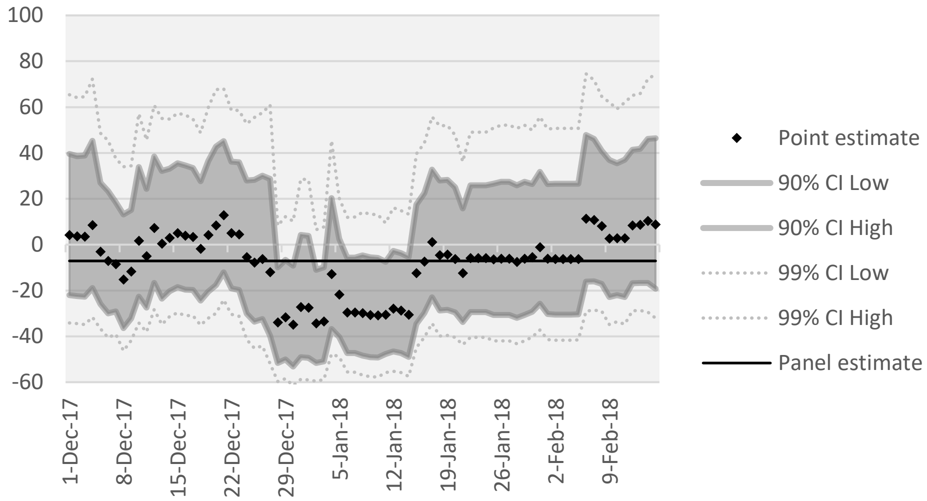
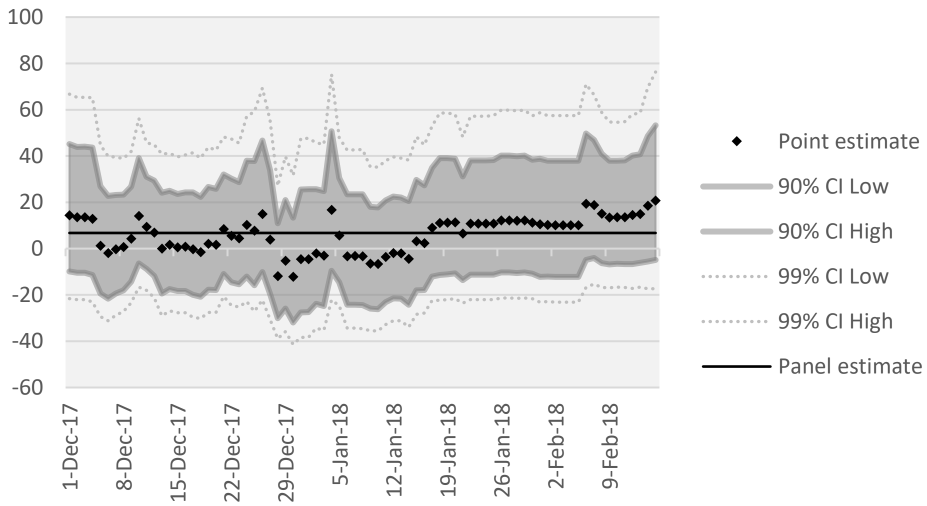
Appendix A. Price premiums for various sparkling wine attributes

Table A.1. Price premium for the attribute “Single grape”



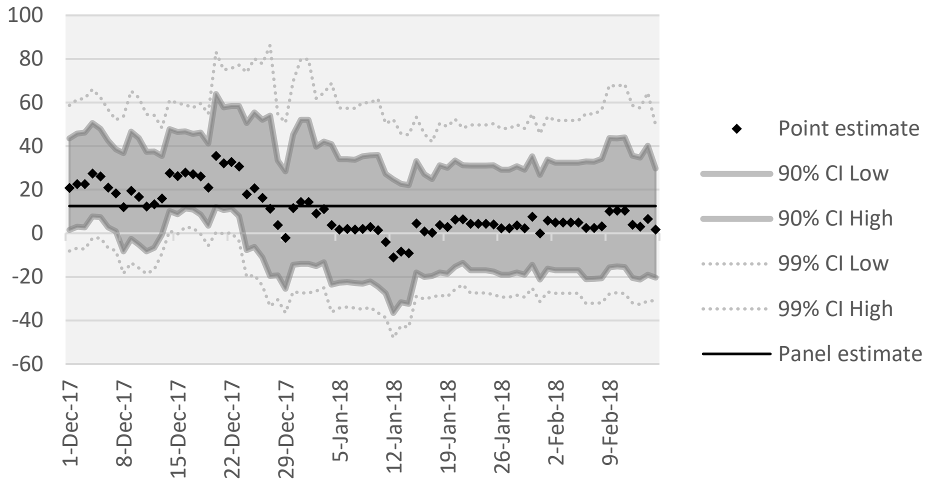
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – products with no information on grape sorts available.

Table A.2. Price premium for the attribute “Cuvée”



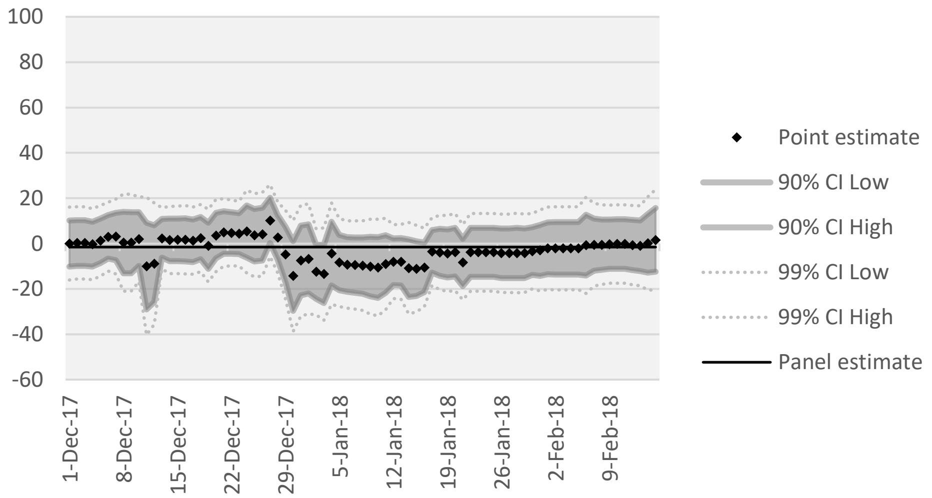
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – products with no information on grape sorts available.

Table A.3. Price premium for the attribute "Origin"



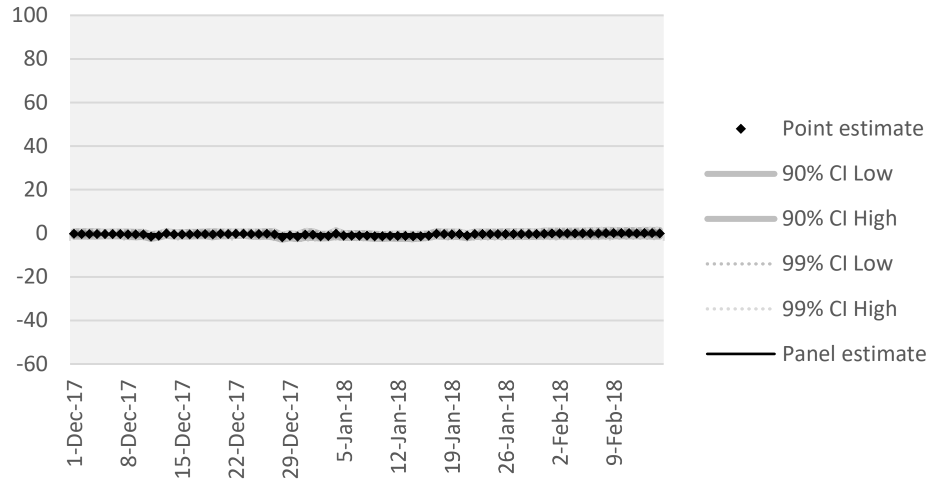
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – a product without geographical designation indicated.

Table A.4. Price premium for the attribute "Rating: number of stars"



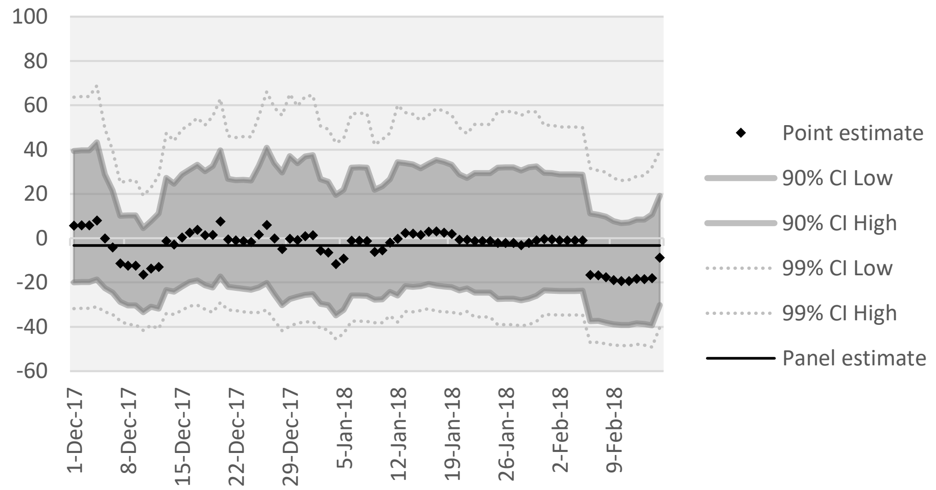
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time.

Table A.5. Price premium for the attribute "Rating: number of evaluations"



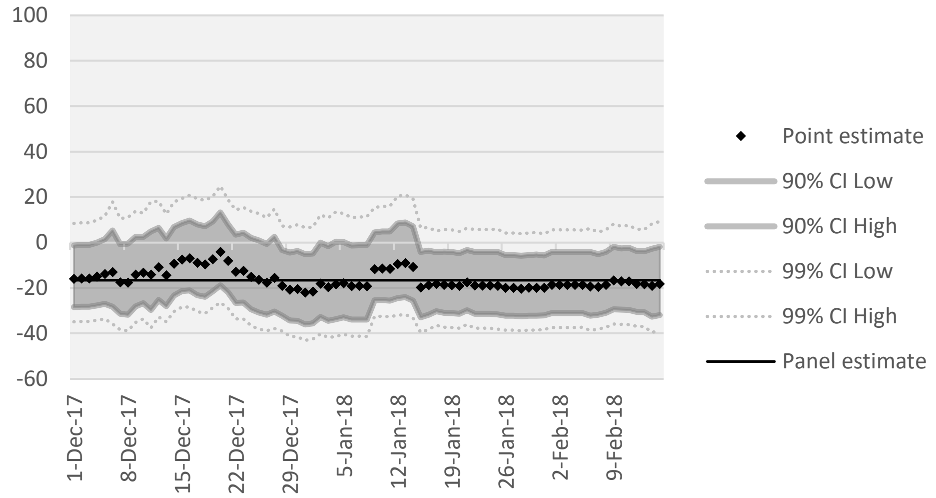
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time.

Table A.6. Price premium for the attribute "Semi-dry"



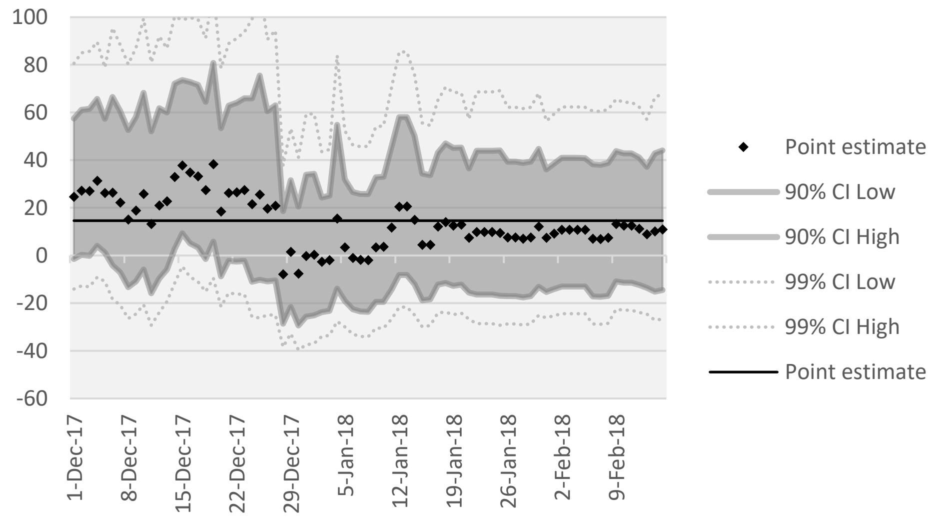
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – dry sparkling wines.

Table A.7. Price premium for the attribute “Semi-sweet”



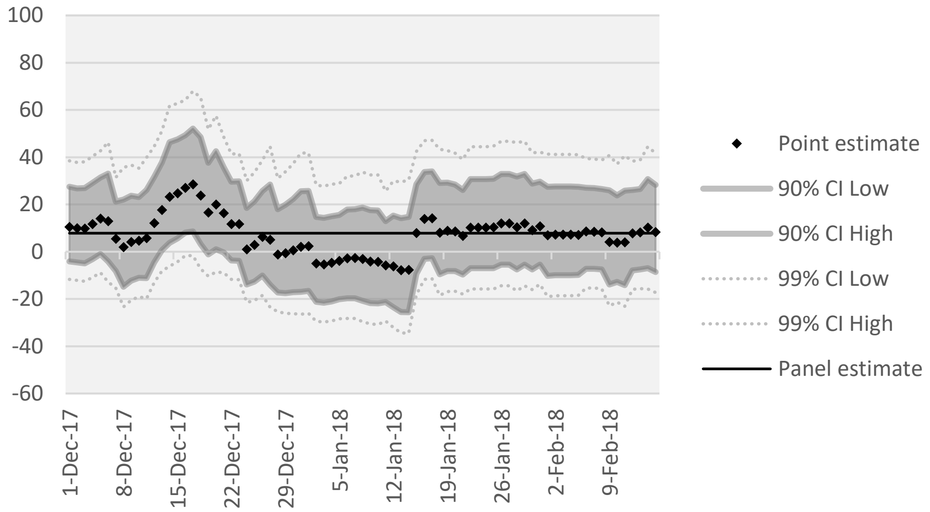
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – dry sparkling wine.

Table A.8. Price premium for the attribute “Sweet”



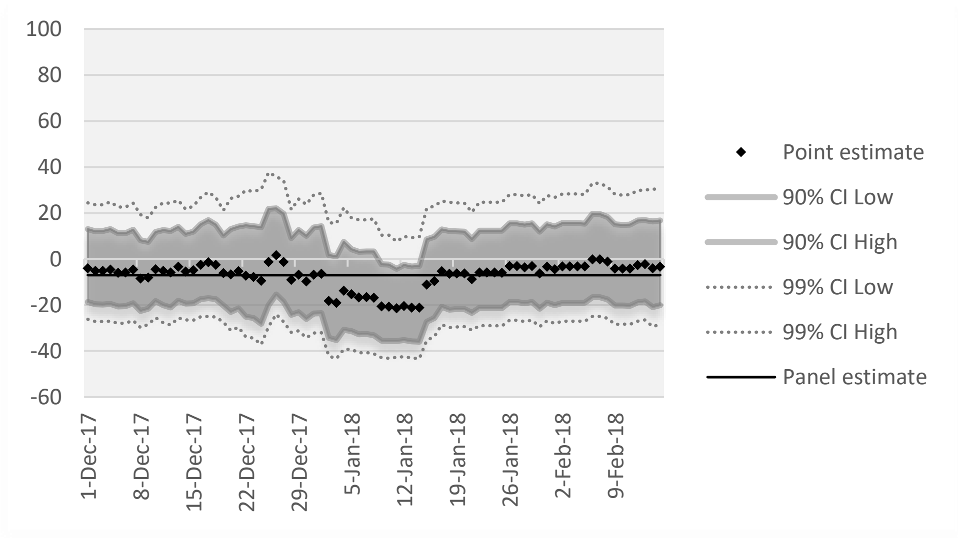
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – dry sparkling wine.

Table A.9. Price premium for the attribute “Rosé”



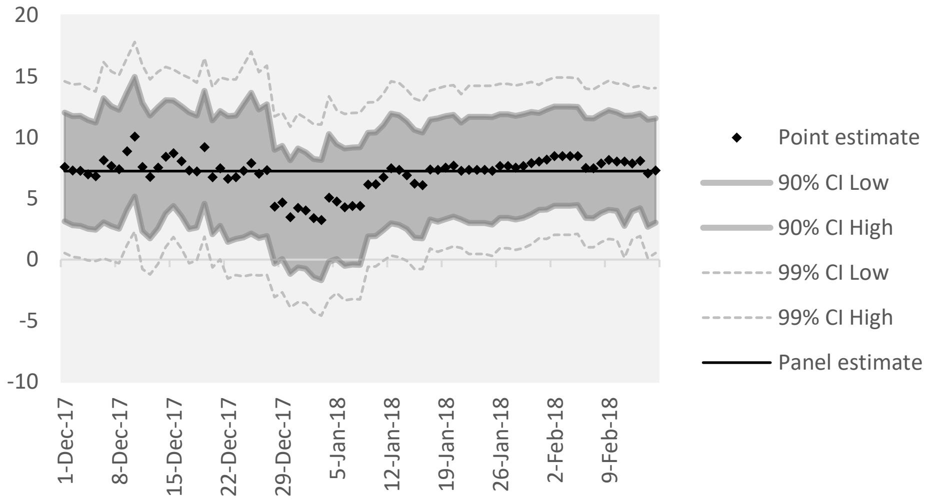
Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – white sparkling wine.

Table A.10. Price premium for the attribute “Red”



Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. To arrive at price effect in % the method by Halvorsen and Palmquist (1980) was used. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time. Reference group – white sparkling wine.

Table A.11. Price premium for the attribute “Alcohol content”



Notes: Each dot corresponds to a respective coefficient from a hedonic function estimated for each day of the period December 1, 2017, to February 15, 2018. The black solid line depicts the estimate from the panel regression, which assumes that consumer evaluation for attribute does not change over time.