

WTP 4 WEO

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February 28, 2017

Abstract

We specify a structural demand model for wine products given a score release field experiment to estimate the consumers' willingness to pay (WTP) for expert opinion labels. We use monthly product level data before and after a retail field experiment in which we treat a random subset of wine products in one treated store and do not treat those same products in comparable control stores. We combine these scanner data with additional information on the characteristics of each product, such as, varietal, region of production, price point relative to other wines, to estimate a structural demand model for wine, defined as a bundle of attributes among which a score that is experimentally introduced into the market. Given the random coefficient structural wine demand estimates we find that wine products in our sample are overall elastic. We estimate that, on average, consumers' WTP for a 83 scored bottle of wine is 2 dollars. Consumers also value California wines by one dollar more than non California wines in the sample, and the Chardonnay varietal has the highest WTP of 2.9 dollars a bottle, while the lowest estimated WTP is for the Merlot varietal. Welfare estimates from alternative attribute space choice sets are obtained via counterfactual simulations to estimate the changes in consumer surplus resulting from available quality information in the form of expert opinion scores, and we estimate there to be a significant welfare loss eliminating scores of 179 dollars which represents roughly one percent of total wine revenue in the treated store.

Keywords: Field experiment, Labels, information, expert opinion, wine, product attributes, structural random coefficients Logit demand, willingness-to-pay.

JEL Classification: M30, Q18, Q25, Q21, C12, C24.

1 Introduction

Given asymmetric information on product quality, consumers know less than producers about the quality distribution of products in their available choice sets and must infer quality based

*WTP 4 WEO = Willingness to Pay for Wine Expert Opinions. Bonnet: Toulouse School of Economics, INRA, University of Toulouse I Capitole; Hilger: U.S. National Marine Fisheries Service; Villas-Boas: Department of Agricultural and Resource Economics, University of California, Berkeley, CA, 94720. We thank Michelle Scizak, Reed Johnson, and Steve Flaming for help with the data; Will Liu and Jeff Coronado for help with the experimental implementation; and Kyle Birchard, Elizabeta Perova, Grant Chen, Patricia Javier, Katan Patel, and Elizabeth Creed for their excellent research assistance. The authors acknowledge the financial support received from the Giannini Foundation. Corresponding author: sberto@berkeley.edu.

on observable attributes at the time of purchase. High quality is typically positively correlated with higher average prices in many markets (Rao, 2005; Shiv et al., 2005). Evidence from blind taste settings in the wine market has consumers attributing a positive premium to wines that are perceived by them as having better quality (add main cites TBA) and Bonnet et al (2016) show that uninformed consumers purchases are consistent with beliefs that high quality is positively related to wine prices. Yet those beliefs may be wrong and consumers might purchase products of less quality they would have had they more information. In many markets, experts provide additional insights about the quality of products they evaluate and attribute expert ratings or scores that are commonly available to consumers. Producers value expert opinion if they are able to charge higher prices for their products, as they use the released scores as a product differentiation device and thus increase market power (e.g., for wine see Ali et al, 2008) and their ability to charge higher prices for wines perceived as having high quality. On the contrary, whether consumers value expert opinion information in this setting remains an unanswered question. This paper uses a randomly assigned introduction of expert opinion scores into the wine market to estimate demand and infer the implied revealed preference willingness to pay (WTP) for expert opinion information in the form of scores.

The contribution of this paper is to provide structural demand estimates of wine products as a function of wine attributes such as price, region of production, varietal, brand, and expert opinion scores using consumer purchase data, that is, using revealed rather than stated choices. The revealed choices has the advantage of facevalidity as it is consumers actual choices faced with real constraints on their own resources and the options available (Hensher et al., 1998; Whitehead et al, 2008). Consumers then individuals consider the

internal costs and benefits of their actions and experience the consequences of their actions. Choices based on the perceived costs and benefits better reflect the values of the population and allow more valid estimates of willingness to pay. Carson et al. (1996) indeed show, in their meta-analysis, that estimates from stated and revealed preferences are different. We also extend our own previous research, where we use the same data to show reduced form demand effects on demand (Hilger et al, 2011) and to test belief updating mechanisms behind the reduced form changes in demand for treated, untreated with scores, and un-scored wine products (Bonnet et al, 2016), namely, by, in this paper, attributing a value to the revealed information and to different levels of quality grades in the form of numeric scores from 50 to 100. The lack of previous research estimating the value of expert scores, be it in wine or other markets, is related to the challenge of identifying unbiased demand responses to scores that are uncorrelated with other strategic decisions taken by firms, such as pricing, branding, and product portfolio assortment choices. This challenge is circumvented in this present paper given that the treatment of wines by revealing their scores is randomly assigned among the potential scored wine products and is completely uncorrelated with marketing variables of the different wine producers and the retailer. When we ran the experiment, neither the retailer, nor the producing vineyards adjusted their marketing variables to take into account the score information.

Using the experimental variation and detailed product attribute data we estimate a structural demand model to infer consumer WTP for wine attributes and WTP for expert opinion labels when making retail product wine purchase choices. Given product level panel scanner data set for months preceding and during the field experiment, for the treated and control stores, we estimate consumer preferences for products by projecting each wine

product into the attribute space, consisting of price, brand, varietal, and displayed scores. Based on consumers' choices we estimate a demand model for the products perceived as a bundle of all the observable attributes and given those demand estimates are able to assign a dollar value to each product attribute. We also simulate what would have been consumers' choices in the absence of the experimentally displayed scores, estimate the resulting welfare change and, in so doing, obtain a welfare estimate of revealing information in the form of expert opinion scores, given all other attributes remaining unchanged.

Related empirical literature has analyzed the extent to which product quality information affects consumer behavior including branding (Montgomery and Wernerfelt, 1994), mandatory product labeling (Jin and Leslie, 2003; Kiesel and Villas-Boas, 2007), experimental labeling (and Kiesel and Villas-Boas, 2008), and advertising (Ackerberg, 2001; Ackerberg, 2003). Closely related to our paper, besides Hilger et al. (2011) are papers by Sorensen and Rasmussen (2004) for the book market and Reinstein and Snyder (2005) for the movie industry. The key identification of the effects of expert opinion on movie demand in Reinstein and Snyder (2005) results from exploiting the timing of movie reviews by Siskel and Ebert. While they find no overall effect of reviews, they show that positive reviews increased box office revenues for narrowly-released movies and dramas, although it remains to be explained why. In the book industry, Sorensen and Rasmussen (2004) find that both positive and negative reviews in the New York Times increase book sales. Our major contribution extending all previous work is that we are the first to assess demand side valuation of expert opinion labels using actual point of purchase decisions of consumers in a field experiment setting. We utilize a flexible discrete choice model (e.g. Berry, Levinsohn and Pakes, 1995; McFadden and Train, 2000; Nevo, 2000; Nevo, 2003; Swait et al, 2004) that incorporates

heterogeneity in demand. The framework allows the empirical testing of the null hypothesis that the displayed expert opinion scores are not valued by consumers.

Our estimates suggest most of our wines to be elastic, given the random coefficient structural wine demand estimates. We estimate that consumers value a score unit by about 2.5 cents, which means that, on average, consumers' WTP for a 83 scored bottle of wine is 2 dollars. In terms of wine varieties, consumers are WTP one dollar more for California wines than non California wines in the sample. The other varieties are also valued, positively, and the Chardonnay variety has the highest WTP of 2.9 dollars a bottle, while the lowest estimated WTP is for the Merlot variety. Using counterfactual simulations, we estimate there to be a significant welfare loss eliminating scores of 179 dollars which represents 1.1 percent of total revenue in this store.

The remainder of the paper is structured as follows. Section 2 presents the data and experimental variation used. Section 3 specifies the structural demand model and derives how to obtain the implied estimates of consumer valuation for expert opinion scores. Section 4 presents and discusses the structural estimates and performs counterfactual simulations to estimate consumer surplus changes of displaying expert scores. Section 5 concludes.

2 The Experiment and the Data

Wine scores from a proprietary wine scoring system were displayed in the treatment store for four weeks during the month of April 2006. Using a proprietary score wine dataset, we labeled 101 wine products with scores in the treated store, which corresponds to displaying scores for about 14% of the wines in the consumers' choice set. Each label features the name

of the proprietary scoring system and the wine's score that, in theory, ranges from the lowest 50 to the highest score of 100, but scores less than 70 are not released by the rating agency.

Figure 1 displays, on the left panel, the kernel density of the score distribution for treated wines in the treated store and depicts the kernel density of the score distribution of the products sold in the control stores that were not labeled, on the right panel, given that we can see the same products in the control stores. Given a Kolmogorov-Smirnov (KS) test for equality of the distributions, we cannot reject the equality of scores distribution. There is therefore a nice match in the whole distribution of labeled wines in the treated and in the control stores.

The treated store is in the same marketing division as a set of 38 potential control stores. What this means is that the pricing, promotion, and display layout is common among all these stores, contributing to a good balance of observable determinants of quantities of wine sold that originate from the retail marketing strategy.

2.1 The Data

We use a weekly by store scanner dataset for treated wine products in the treated and in 4 control Northern Californian stores that better match the treated store in terms of pre-period trends in labeled wines. The data provide an unique wine product code identifier (UPC), the name of the wine including varietal, the number of bottles sold, the pre-discount price paid, and any retail discount pricing offered. We aggregate the weekly sales data to the month-level for each store to generate the total number of bottles sold per month, average shelf price, average price paid (the shelf price net of discounts), and whether a bottle of wine was discounted during the given month. Pricing and discounting for each product are

common for all the stores in the data and, moreover, wine pricing was not updated due to the selection of products into labeled and unlabeled status, and finally prices were not differentially updated in the treated store due to our experiment.

For those wines for which proprietary wine score data exist, we then merge the wine score data into the scanner data. In addition we collect a detailed product attribute dataset, identifying brand of the wine product, varietal, red, white, or other, origin of production, imported status that we also merge with the scanner dataset.

Summary statistics for the data used in the analysis are reported in Table 1. In the first column we report descriptive statistics for the treated store and in column 2 for the control stores. In the first row we report average quantity sold during the pre-treatment, in the next row, its standard deviation and then, below that, average quantity sold during the treatment month (April), followed by its standard deviation. Average quantity sold by product in March is 17 bottles for labeled wines in the treated store and 10 bottles in the control stores on average. Average prices in March as well as in April, are 11 dollars for treated wines and those averages are not statistically different between treated and control stores. Most of the wine consumers purchase is discounted in March and also in April, namely 90 percent for treated wines in both treated and control stores.

The bottom part of Table 1 reports average and the standard deviation of scores for treated and control stores. Here we see that average scores are around 83.13 for treated wines and Figure 1 already attested to not only similar average scores but also very similar score distributions for the treated and control stores.

In the treated store and control stores there are 58 percent red wines in the treated group. In terms of the percentage of white wine the proportions are also very similar in the treated

and controls stores.

In the treated store, we have data on 2562 product month observations for treated wine products while in the four control stores the total number of observations is 11058 for the treated wine products.

2.2 Trends and Wine Market Shares in Treated and Control Stores

Given the total quantity Q sold of wine by month by store we construct product market shares by dividing each product's quantity sold by the total quantity Q . In Figure 5 we depict the kernel density estimates of the market share of treated wine products in the treated and in the control stores. We see that at most a wine product represents 8 percent of total wine sales in a month in a store, and the densities are very similar between treated and controls stores but we reject equality of both distributions given a K-S test.

To estimate the causal effect of revealing score on consumer demand and valuation, a crucial feature is that there are similar pre period trends of quantity sold and market shares for products in the treated and the control stores used in the analysis. Figure 3 shows trends in the sum of the monthly market shares of labeled products in treated and in the controls stores. It shows that the trends are quite similar in the treated and control store which will allow us to investigate the causal effects of the display of labels on treated wines on demand choices and infer from that WTP for those displayed scores.

3 Consumer Demand Model

Using two data sets, a store level and a product characteristics data set, we estimate a structural revealed preference model of consumer demand. We estimate the latent willingness

to pay of consumers for product labels providing expert opinion information on product quality. Modeling consumer choice as the demand for product bundle of observable attributes we are able estimate the a dollar value of each standard attribute. Values of consumers willingness to pay for expert opinion information are empirically estimated through the incorporation to model of an additional expert opinion variable which is introduced through a field experiment.

3.1 *Structural Demand Model*

Taking advantage of these unique data we are able to access consumer valuation of the expert opinion quality label in a discrete choice model (McFadden, 1974; Train, 2002) approach. In this context, we define product specific information provision via expert opinion labels as additional or differentiated product attributes. We further define the consumer product as a bundle of perceived product attributes, which allows us to compute consumer's willingness to pay for additional labeling information in a straightforward way. The utilized discrete choice model (e.g. Berry, Levinsohn and Pakes, 1995; McFadden and Train, 2000; Nevo, 2000; Nevo, 2003; Swait et al, 2004) also offers flexibility in incorporating heterogeneity.

Starting from a random utility framework (e.g. McFadden 1974; and Train, 2002) where both the product attributes as well as a random term are assumed to enter linearly, the utility from consuming a certain product j , where a product is defined as a certain wine UPC sold at a certain store, can be described as

$$(1) \quad U_{ijt} = \alpha_j - \beta_i p_{jt} + X_{jt} \beta_x + \gamma T_{jt} \text{Score}_{jt} + \xi_{jt} + \varepsilon_{ijt},$$

where α_j is a product (UPC-Store) fixed effect capturing the intrinsic preference for product j . The shelf price of product j at month t is denoted by p_{jt} and the marginal utility of price is β_i . In γ we measure consumer's average marginal utility for the labeled score experimentally displayed on product j denoted by T_{jt} and that corresponds to a variable that is equal to the wine score during the treatment period in the treatment stores and equal to zero otherwise, and $Score_{jt}$ is the value of the displayed score for product j . A treated store indicator and treated weeks indicators are included in X_{jt} . The term ξ_{jt} accounts for monthly changes in factors such as shelf space, positioning of the product among others that affect consumer utility, are observed by consumers and firms but are not observed by the researcher. Finally, ε_{ijt} is an i.i.d. type I extreme value distributed error term capturing consumer idiosyncratic preferences.

To allow for category expansion or contraction, we include an outside good (no-purchase option), indexed by $j = 0$, whose mean utility is normalized to zero and therefore its utility is given by the idiosyncratic term only, namely,

$$(2) \quad U_{i0t} = \varepsilon_{i0t}.$$

The price coefficient β_i is assumed to vary according to

$$(3) \quad \beta_i = \beta + \sigma v_i, \quad v_i \sim N(0, 1),$$

where β and σ are parameters to be estimated.

As in Nevo (2000) we rewrite the utility of consumer i for product j as

$$(4) \quad U_{ijt} = \delta_{jt}(p_{jt}, X_{jt}, \xi_{jt}; \alpha, \beta, \beta_x \gamma) + \mu_{ijt}(T_{jt}, v_i; \sigma) + \varepsilon_{ijt},$$

where δ_{jt} is the mean utility, while μ_{ijt} is the deviation from the mean utility that allows for consumer heterogeneity in the price response.

Let the distribution of μ_{ijt} across consumers be denoted by $F(\mu)$. Then the aggregate probability S_{jt} of product j at month t across all consumers is obtained by integrating the consumer level probabilities:

$$(5) \quad S_{jt} = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{n=1}^N \exp(\delta_{nt} + \mu_{int})} dF(\mu).$$

This aggregate demand system not only accounts for consumer heterogeneity, but also provides more flexible aggregate substitution patterns than the homogeneous logit model. When estimating demand, the goal is to derive parameter estimates that produce product market shares close to the observed ones. This procedure is non-linear in the demand parameters, and prices in general enter as endogenous variables, although prices are not set at the product month store level, rather prices are set at the wine price division level that covers all of the stores in the sample. We will treat prices as exogenous to wine UPC by month by store level determinants of demand given that prices are decided at a more macro level than that.

We estimate the random parameters logit demand model from product (UPC-store) monthly market shares using GMM-estimator proposed by Berry Levinsohn and Pakes (1995)

and Nevo (2001), allowing for consumer heterogeneity in the valuation of product characteristics, that can be explained by variation a normal random variable given that we do not have demographic variables.

We follow Berry (1994) who constructs a demand side equation that is linear in the parameters to be estimated. This follows from equating the estimated product market shares¹ to the observed shares and solving for the mean utility across all consumers, defined as

$$(6) \quad \delta_{jt}(\alpha, \beta, \beta_x \gamma) = \alpha_j - \beta p_{jt} + X_{jt} \beta_x + \gamma T_{jt} \text{Score}_{jt} + \xi_{jt}.$$

For the mixed Logit model, solving for the mean utility (as in Berry 1994) has to be done numerically (see Berry, Levinsohn, and Pakes, 1995 and Nevo, 2001). Finally, once this inversion has been made, one obtains equation (6) which is linear in the parameter associated with all wine attributes and the estimates are obtained by a fixed effects OLS regression. If we let θ be the demand side parameters to be estimated, then $\theta = (\theta_L, \sigma_{Price})$ where θ_L are the linear parameters $(\alpha, \beta, \beta_x, \gamma)$ and σ_{Price} is the non-linear price parameter. In the mixed Logit model, θ is obtained by feasible Simulated Method of Moments (SMOM) following Nevo's (2000) estimation algorithm, where equation (6) enters in one of the steps.²

The demand model represents consumer choice between different wine products over time,

¹For the random coefficient model the product market share in equation (4) is approximated by the Logit smoothed accept-reject simulator.

²The aim is to concentrate the simulated GMM objective function such that it will be only a function of the non-linear parameters. By expressing the optimal vector of linear parameters as a function of the non-linear parameters and then substituting back into the objective function, it can be optimized with respect to the non-linear parameters alone.

where a product is perceived as a bundle of attributes, among which scores and price. A product-store fixed effect is included to capture observed and unobserved product constant product (UPC-Store) factors that affect demand. The econometric error that remains in ξ_{jt} will therefore only include the (not-product specific) changes in unobserved product characteristics such as unobserved consumer level determinants of demand.

3.2 Estimating Average and Heterogeneous Marginal Utility, WTP, and Price Elasticities

Using the dataset of product choices, we estimate a random coefficients Logit choice model given by (6) of consumer demand for the wine products in the sample, where each product is defined as a bundle of attributes, including price, a product fixed effect, and score variable that varies experimentally due to the random treatment. We obtain estimates of average willingness to pay for the labels by dividing the estimates for γ by the average marginal utility of price β to obtain an average willingness to pay for each product label claim, given store level observed purchases.

Given the demand estimates we obtain estimates for the predicted market shares of each wine product j for draw i by

$$(7) \quad \hat{s}_{jit} = \frac{\exp(\hat{\alpha}_j - \hat{\beta}_i p_{jt} + X_{jt} \hat{\beta}_x + \hat{\gamma} T_{jt} \text{Score}_{jt})}{1 + \sum_{n=1}^N \exp(\hat{\alpha}_n - \hat{\beta}_i p_{nt} + X_{nt} \hat{\beta}_x + \hat{\gamma} T_{nt} \text{Score}_{nt})}.$$

The market share is obtained by averaging (7) over all the normal draws, that is, given by $s_{jt} = \frac{1}{R} \sum_{i=1}^R s_{ijt}$, where R are the number of normal draws of v_i . Given the demand parameters and market shares in (7) we obtain the resulting estimates for the own price elasticities for all the products in our sample for the treated and the control stores by averaging

over the draws as

$$(8) \quad \hat{\eta}_{jj,t} = \frac{\delta s_{jt} p_{jt}}{\delta p_{jt} s_{jt}} = -\frac{p_{jt}}{\hat{s}_{jt}} \frac{1}{R} \sum_{i=1}^R \hat{\beta}_i \hat{s}_{ijt} (1 - \hat{s}_{ijt}).$$

3.3 Estimating Consumer Welfare Changes in Policy Simulations

Estimates of changes in consumer surplus (CS) are derived through simulation of consumer choices under counterfactual attribute composition of their choice sets. These correspond to a respondent's compensating variation for a change in product attributes (Small and Rosen, 1981). The expected consumer surplus, CS_i , is defined as

$$(9) \quad CS_i = \frac{1}{|\beta|} \ln \sum_j e^{\alpha_j + X_{jt}\beta_x - \beta_i \text{price}_{jt}},$$

where β denotes the average marginal utility of price. We estimate the Consumer surplus for the baseline choices when scores are displayed, and then the consumer surplus for the next best alternatives consumers choose when there is no longer score information available. The distribution of estimated changes in consumer surplus are then obtained, and we estimate the average change in consumer surplus from eliminating the available information in the form of scores in the treated store as

$$(10) \quad \Delta CS = \sum_i \Delta CS_i.$$

where CS_i is given by (9) and ΔCS is Total Consumer Surplus without Scores minus

Total Consumer surplus with Scores.

4 Results

This section is organized as follows. First we present simple Logit model estimation results and then the more flexible Random Coefficients Logit specification results in terms of marginal utilities and price elasticities for all the wine products in treated and control stores. Finally, given demand, we estimate the average WTP for observable wine attributes, and then we compute the welfare consumer surplus changes in counterfactual simulations using the structural demand model, when removing the scores.

4.1 Structural Demand Results - Logit Marginal Utilities for Wine Attributes

The logit specification forces $\sigma = 0$ in the heterogeneity specification of the marginal utility of price in (3) resulting in equation (6) being estimated in a straightforward fashion. The simple Logit marginal utility estimates are presented in Table 2, where the dependent variable is the log share of a product j sold in a store during month m minus the log of the share of the outside option. We obtain the outside option share as the difference, for every choice occasion (store month, that is) between 100 percent and the sum of the market shares of the treated wine products in the choice set. In Column (1) the right hand side variables are any observable and unobservable characteristics at each wine product level (via a Product Fixed Effect), constant characteristics of the treated store (in the form of the “Treated Store” indicator), changes in demand factors at the time of the treatment common to both the treatment and control stores (“Treated Period” indicator) and, finally as a function of changes due to the treatment in the treated store relative to changes in the controls

(“Treatment Store X Treated Period”). In column (2) we add price and a discount dummy to the specification in (1). Adding Price and discount indicator improve the R squared, and the marginal utility of price is negative and significant, -0.164, while the marginal utility of discounts is positive and significant, 0.539. In column (3) we add the score each an additional variable interacted as “Score X Treated Store X Treated Period”. While the treatment has an overall negative marginal utility -0.207, the higher the scores, the larger the treatment marginal utility, given the positive and significant marginal utility of 0.003. Therefore, in the treated store relative to controls consumers like the new information more the higher scores when making their choices.

Given that we have product fixed effects, all of the product characteristics that are time invariant, like brand, varietal, red and white, are collinear. To obtain the marginal utilities with respect to those attributes we regress the estimated product fixed effects omitted but included in column (3) in Table 2 on those characteristics. Those estimates are in Table 3. Consumers place a positive and significant marginal utility of 0.597 on California wines, the Cabernet varietal (0.369), a larger marginal utility for the Merlot and Pinot varietals (1.45 and 1.12, respectively), the largest marginal utility is for several white wine varietals, and Rose/ Zinfandel combined category, followed by Gris and Gewurtsminer varietal, while Syrah also receives a positive marginal utility. The other varietals, like Chardonnay, and others omitted due to space are not given significant marginal utilities. Given this information, we turn now to a more general demand specification allowing for heterogeneity in the marginal utility of price that we will use, in turn to normalize all the above described marginal utilities to recover WTP for the wine attributes.

4.2 *Structural Demand Results - Random Coefficient Logit Marginal Utilities and Price Elasticities*

The demand model estimates obtained by GMM as in Reynaert and Verboven (2014), Nevo (2000) and Berry et al, (1995) are presented in Table 4. We estimate demand without (column 1) and with (column 2) varietal fixed effects, price, California region dummy, discount, and treatment store and period interactions and the coefficient of interest, associated with the “Score X Treated Store X Treated Period” variable in the first row. This specification is motivated by the significant marginal utilities obtained in the Logit specification and we obtain the desired coefficients to estimate the WTP in the next section by dividing the marginal utilities of all the attributes by the marginal utility of price, which is -0.199 and significant. It also has significant heterogeneity given that the estimated sigma is significantly different from zero, given by the bottom coefficient labeled SD Price of 0.1.

With the estimated demand coefficients for the Random coefficients’ Logit model we obtain the estimated own- and cross-price elasticities for all products in the choice given (8). Figure 4 shows the kernel density estimates of the distribution the elasticities for all products in the treated and in the control stores. Most (75.5 %) of the wines’ estimated own price elasticities are greater than one in absolute value, suggesting elastic demand for wine and only 4 (2 percent) of the estimated own price elasticities are positive. Finally, we cannot reject the equality of elasticity distributions between treated and control stores’ wines in the post period.

In terms of the marginal utilities, California wines are liked, as are most varietals, given the positive and significant marginal utilities estimates in column (2) of Table 4. Once again,

consumers place a positive marginal utility on score levels displayed during the treatment period at the treated store, given the significant point estimate of 0.005. What these coefficients “in marginal utilities” mean after being converted into dollars is investigated and discussed next.

4.3 WTP for Wine Attributes and Expert Opinion Experimentally Displayed Scores

We divide all marginal utilities by the average marginal utility of price that, following Train (2003), is assumed as a fixed parameter, and obtain estimates of average WTP as reported in Table 5. Based on these estimates we find an overall positive average consumer willingness to pay for expert opinion scores for each score point of 2.5 cents. Given that the average score displayed is 83, this means that consumers are willing to pay for the average scored wine about 2 dollars more than had they not received the score information. Other attributes amount to significant WTP estimates, in particular, consumers are willing to pay an almost one dollar premium for California wines, and the Chardonnay varietal has the highest WTP of 2.9 dollars, followed by Cabernet of 1.8 dollars, and 1.1 for both Pinot and the Gris/Gewurtzminer combined type. Merlot has a positive albeit not significant WTP estimate based on the purchases of consumers in our data. It does not exist in the literature any work similar to ours, that is assessing the WTP of expert opinion in the wine market. We could find some WTP estimates for some other characteristics deduced from consumer questionnaires. Louriero (2003) used a survey on 100 wine consumers and found small WTP for Colorado wines and environmentally friendly wines, 4 and 17 cents respectively. Bazoche et al (2008) found through an experimental study of French wines that the WTP for the effect of information about the pesticide use in farming is 2.3 on average, that is roughly 3

dollars. Sellers-Rubio and Nicolau-Gonzalbez (2016) show that the WTP for sustainable Spanish wines is +12.9% of the price of non-sustainable wines which corresponds to 1.4 dollars if the price is 11 dollars. In the Hong Kong wine market, Song et al (2015) used an hedonic price function to reveal a positive WTP for red wines with respect to white wine, for Old World wines with respect to New World ones or for well-known grape variety.

4.4 Policy Simulation of Removing all Scores' Information

As we estimated, the average scored wine WTP amounted to 2 dollars, testifying to the value consumers place on the expert opinion scores displayed. Here we perform a welfare analysis resulting from having introduced scores into this market using the flexible random coefficients demand model. The procedure is to estimate consumer surplus for choices made when scores are available and then simulate what consumer's choices would be in the absence of scores and estimate the resulting counterfactual consumer surplus. The difference in surplus amounts to the welfare change due eliminating scores. In other words a negative change in surplus when eliminating scores means that scores are significantly valued by consumers, and by adding the total change in Consumer surplus we obtain a total value of displaying the scores in this particular market.

First we estimate the product level market shares of the choices given the estimated parameters for the baseline scores as they are. These are depicted in the top panel of Figure 5. Then we predict the choices made when no scores are available and those are depicted in bottom panels of Figure 5. We see that the mass point at zero increased when no scores are available. Figure 6 aggregates market shares for wine products in the choice set and also for the outside option and reports the changes in shares due to the simulation in outside option

shares as well as inside option shares. What we see is that removing scores had the biggest effect on increasing the outside option. Given that we normalize the mean utility to be zero, this indicates that we will have a welfare loss in this simulation counterfactual. We turn to estimating this loss next.

We investigate formally the changes in respondents' consumer surplus by comparing the baseline and the counterfactual scenario's compensated variation for all respondents. The kernel density distribution of consumer surplus when consumers are faced with the same wine options but now wines are no longer identified according to expert scores, and consumers only see the price, and product constant attributes such as the brand and varietal, is given in Figure 7, as well as the estimated kernel density of consumer surplus for the baseline choices. We see a shift to the left of the density without scores, meaning that there is a higher mass of consumers with lower surplus in the simulated counterfactual than at baseline.

Breaking down the changes in Surplus even further, in Figure 8 we see the histogram of the estimated changes in consumer surplus on the left panel. While there is a mass point at zero, there is a small mass that shows an estimated loss of surplus between -2 and -1.5 dollars. On the right panel, as expected, nothing changes in the control stores in the counterfactual simulations, while the estimated loss in consumer surplus originates in the treated store.

Overall, the visual evidence suggests that this policy experiment of removing expert scores has a net welfare loss. What this means is that scores provided an increase in consumer surplus and welfare.

5 Conclusion

The specific research question addressed in this paper is how much are consumers willing to pay for expert opinion scores and for other observable product attributes of wine in the context of asymmetric information about wine quality. We find that to be so, in that the average WTP for the average score in our sample is 2 dollars.

We also estimate the WTP for other wine attributes consumers see when making purchases. Wines of California origin are valued by 1 dollar more than non California wines. The Chardonnay varietal has the highest WTP of 2.9 dollars a bottle, while the lowest estimated WTP is for the Merlot varietal. According to Nielsen data quoted by the Wine Institute (2014) the most sold wine varietal in the US is Chardonnay (with 20% market share in 2013) while Merlot is somewhat in the middle range varietal, with 9% market share.

When simulating changes in information by removing scores we estimate there to be significant consumer surplus losses in this market, of 178 dollars representing 1.1 percent of the revenues in this market, which suggests that disclosing expert opinions results in small in magnitude but significant positive welfare effects. Extrapolating to the national market, given total US wine retail revenues for 2013 of \$36.3 billion dollars,³ our findings would imply that consumers would be willing to pay up to 363 million dollars for information about quality of wines via expert opinions.

³<http://www.wineinstitute.org/resources/pressroom/04242014>.

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Figure 1: Histogram of Scores of Treated Wines in Treated and Control Stores



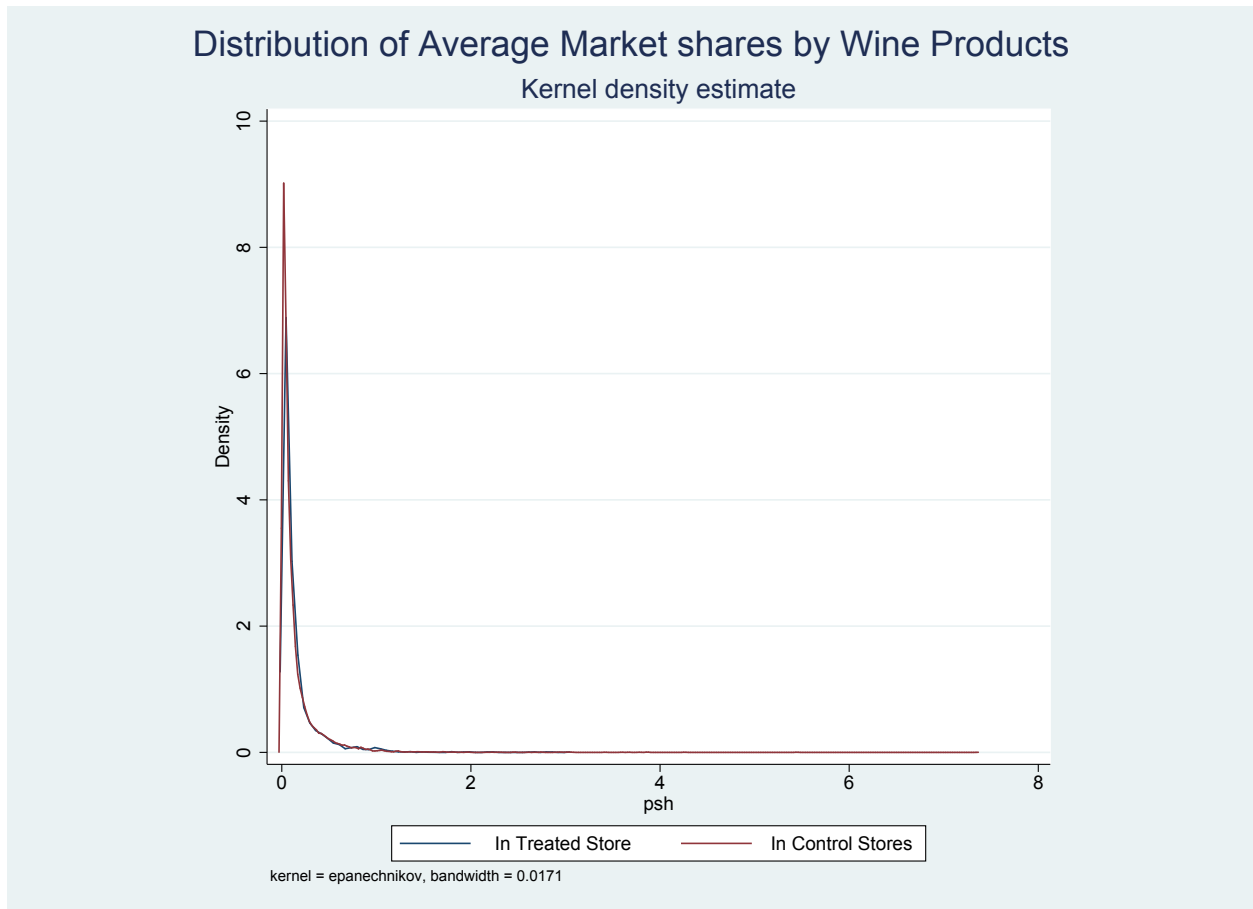
Note: This Figure displays jointly the kernel density estimates of the score distribution for the set of treated products in the treated store and the kernel density estimates of the score distribution in control stores for the same group of wine products treated in the treated store, given that we can see the same products in the control stores. The Kolmogorov-Smirnov (KS) test cannot reject the equality of treated wines scores' distributions in the treated and in the control stores, given that KS is 0.0232 (p value 1.000).

Table 1: Summary Statistics of Wines by Treatment Status for Treated and Control Stores

	(1) Treated Store Treated Wines	(2) Control Stores Treated Wines
Quantity (March)	16.99 (26.01)	11.24 (26.02)
Quantity (April)	14.88 (22.23)	10.97 (22.53)
Price (March)	10.98 (5.00)	11.24 (5.03)
Price (April)	10.96 (5.15)	10.97 (4.83)
% discounted (March)	0.91	0.88
% discounted (April)	0.88	0.89
Score	83.21 (3.28)	83.12 (3.37)
% red	0.58	0.59
% white	0.35	0.34
Number Wines	101	101
Number Observations	2562	11055

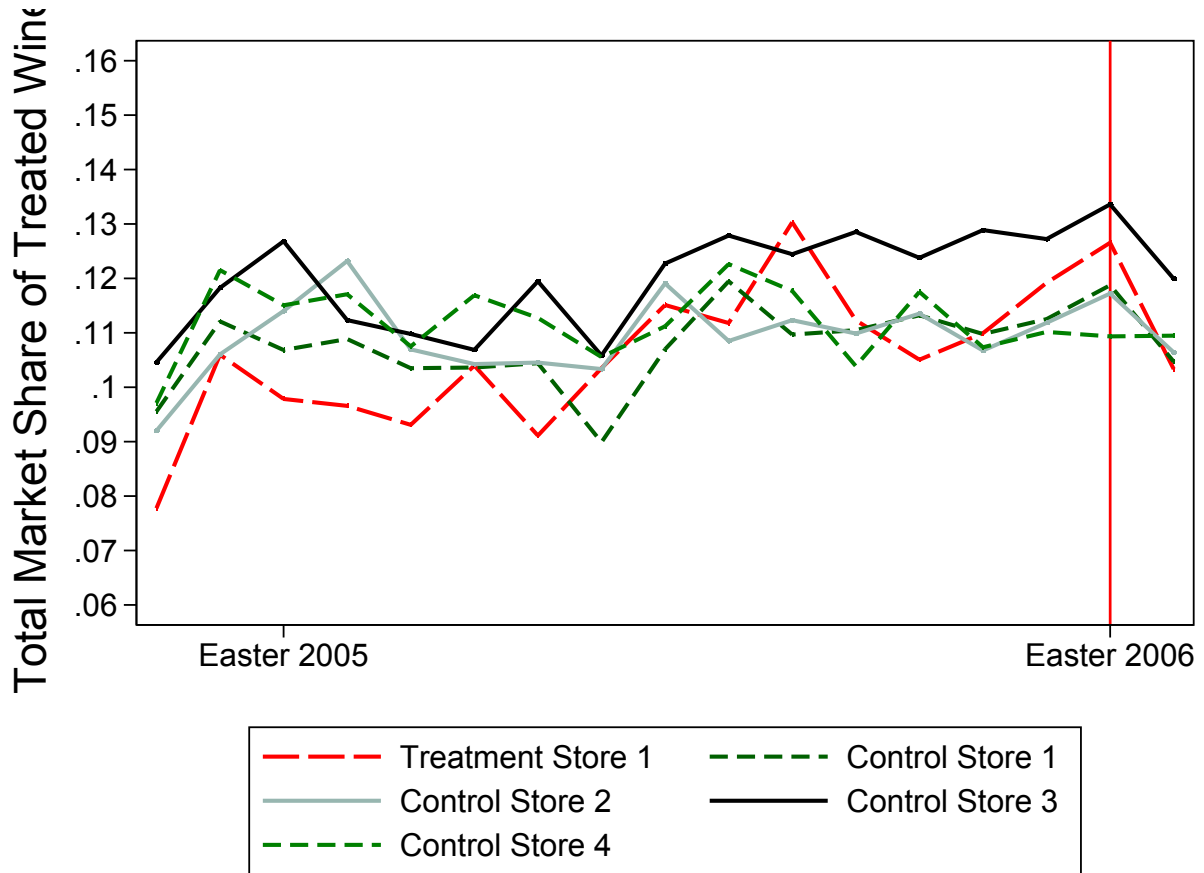
Standard Deviations in parentheses. First column for Treated Store, next for Control stores.

Figure 2: Distribution of Market Shares in Treated and Control Stores



Note: This Figure displays jointly the kernel density estimates of the treated wine product market shares in the treated and in the control store. According to the Kolmogorov Smirnov test we reject the null of equality of both distributions rejected; K-S: 0.0586 p value (0.000). The x axis is in percentages already, and the Maximum market share of a product is less than 8 percent in the treated and control stores.

Figure 3: Trends of Market Shares of Treated Wines in Treated and Control Stores



Note: This Figure displays jointly the evolution of the treated wine product market shares in the treated and in the control stores.

Table 2: Logit Wine Demand Estimates for Treated Wines

	(1)	(2)	(3)
Treated Store X Treated Period	-0.013 (0.073)	-0.008 (0.080)	-0.207** (0.089)
Treated Store	0.033 (0.019)	0.005 (0.020)	0.005 (0.020)
Treated Period	0.058*** (0.019)	-0.047 (0.053)	-0.047 (0.052)
Price		-0.164*** (0.010)	-0.164*** (0.010)
Discount Dummy		0.539*** (0.039)	0.538*** (0.039)
Score Level X Treated Store X Treated Period			0.003*** (0.000)
Mean of Dep. Variable	-7.190	-7.190	-7.190
Num of Obs.	13617	13617	13617
R squared	0.515	0.603	0.603
Product FE	X	X	X

Clustered errors in parentheses at the month level. Controls are best 4 stores. The dependent variable is the $\ln(\text{market share of product}) - \ln(\text{share of outside option})$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Logit Wine Demand Estimates for Constant Attributes

	(1)
	Estimated Marginal Utilities
California	0.597*** (0.000)
Cabernet	0.369* (0.196)
Chardonnay	0.598 (0.357)
Merlot	1.450*** (0.304)
Pinot	1.120*** (0.195)
Syrah	0.908*** (0.196)
Several Whites	2.206*** (0.368)
Gris/ Gewurztrminer	1.444*** (0.299)
Rose /Zinfandel	1.760*** (0.344)
Mean of Dep. Variable	-1.757
Num of Obs.	75
R squared	0.874
Brand FE	X

The dependent variable are the estimated fixed effects from Logit Specification
 $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

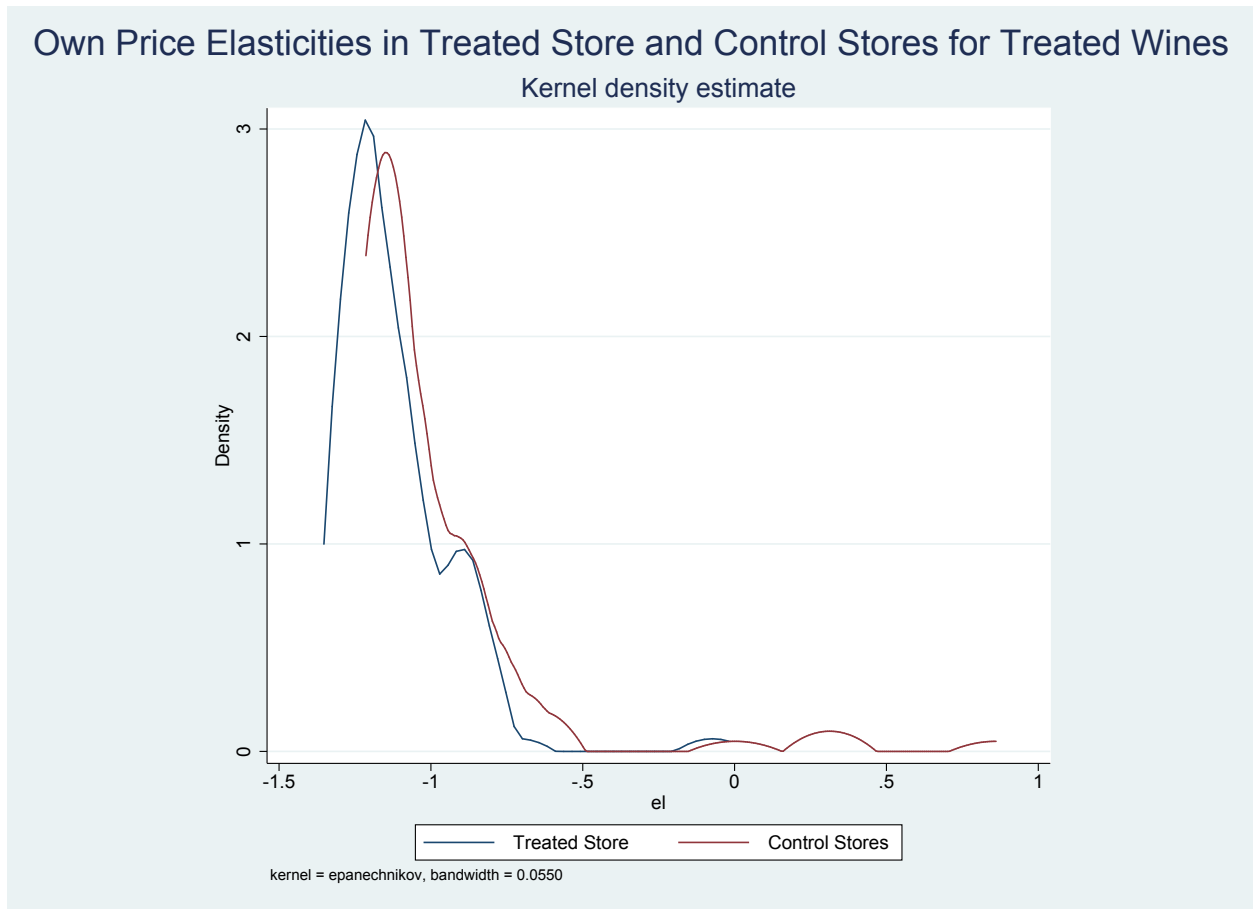
Table 4: Random Coefficient Logit Wine Demand Estimates for Treated Wines

	(1)	(2)
Score Level X Treated Store X Treated Period	0.005* (0.003)	0.005* (0.003)
California	0.285*** (0.043)	0.192*** (0.027)
Discount Dummy	0.921*** (0.029)	0.923*** (0.025)
Treated Store X Treated Period	-0.334 (0.206)	-0.329* (0.197)
Treated Store	0.017 (0.026)	0.007 (0.024)
Treated Period	-0.097** (0.042)	-0.096** (0.040)
Price	-0.193 (0.120)	-0.199*** (0.019)
Cabernet		0.357*** (0.121)
Chardonnay		0.583*** (0.114)
Merlot		0.134 (0.115)
Pinot		0.224* (0.129)
Gris/ Gewurztniner		0.220* (0.118)
Price		
SD	0.099* (0.058)	0.100*** (0.009)
Simulated GMM	3.146e-17	1.872e-18
Num of Obs.	13617	13617
Varietal FE		X

Clustered errors in parentheses at the month level. Controls are best 4 stores.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Distribution of Estimated Own Price Elasticities in Treated and Control Stores



Note: This Figure displays jointly the kernel density estimates of the treated wine product estimated Own Price Elasticities in the treated and in the control store. The Kolmogorov Smirnov test for equality of both distributions cannot be rejected (p value 0.9999). Elasticities are based on the estimates in Table 4.

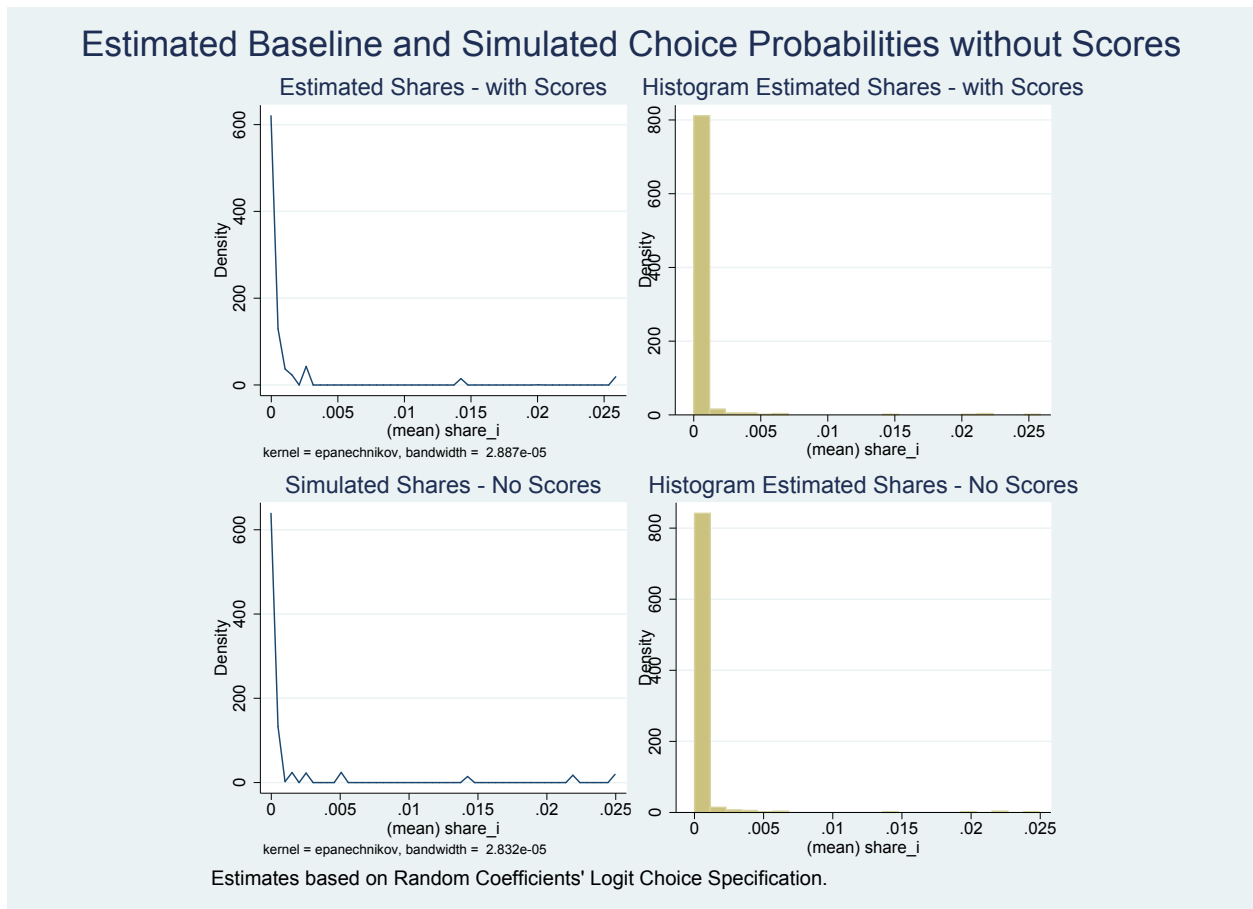
Table 5: WTP for Attributes of Treated Wines

	WTP
Score	0.025 * (0.015)
California	0.965 *** (0.136)
Cabernet	1.794 *** (0.608)
Chardonnay	2.930 *** (0.573)
Merlot	0.673 (0.578)
Pinot	1.126 * (0.648)
Gris/ Gewurztraminer	1.106 * (0.593)

Standard errors in parentheses. Estimates based on Table 4.

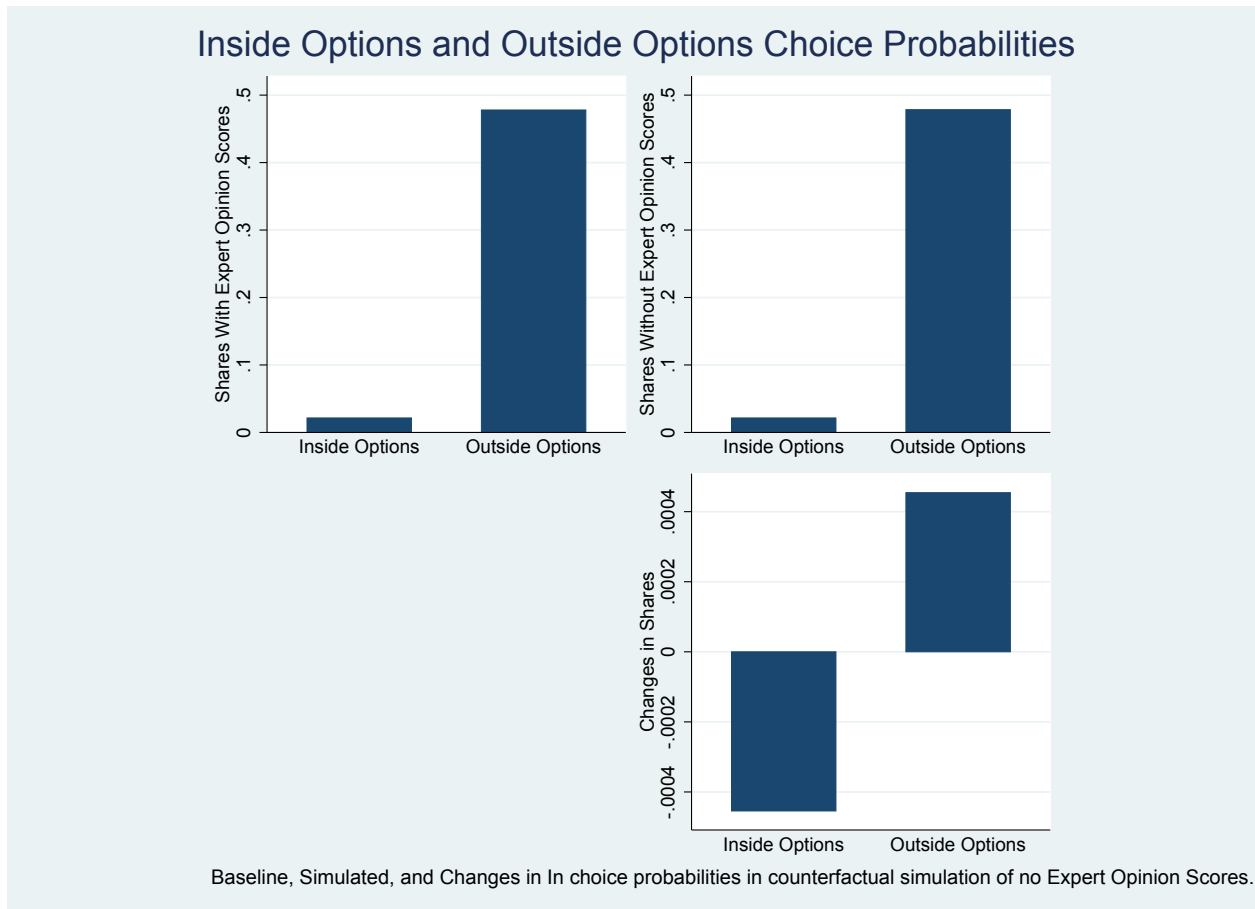
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Distribution of Estimated Choice Probabilities in With and Without Expert Opinion Scores



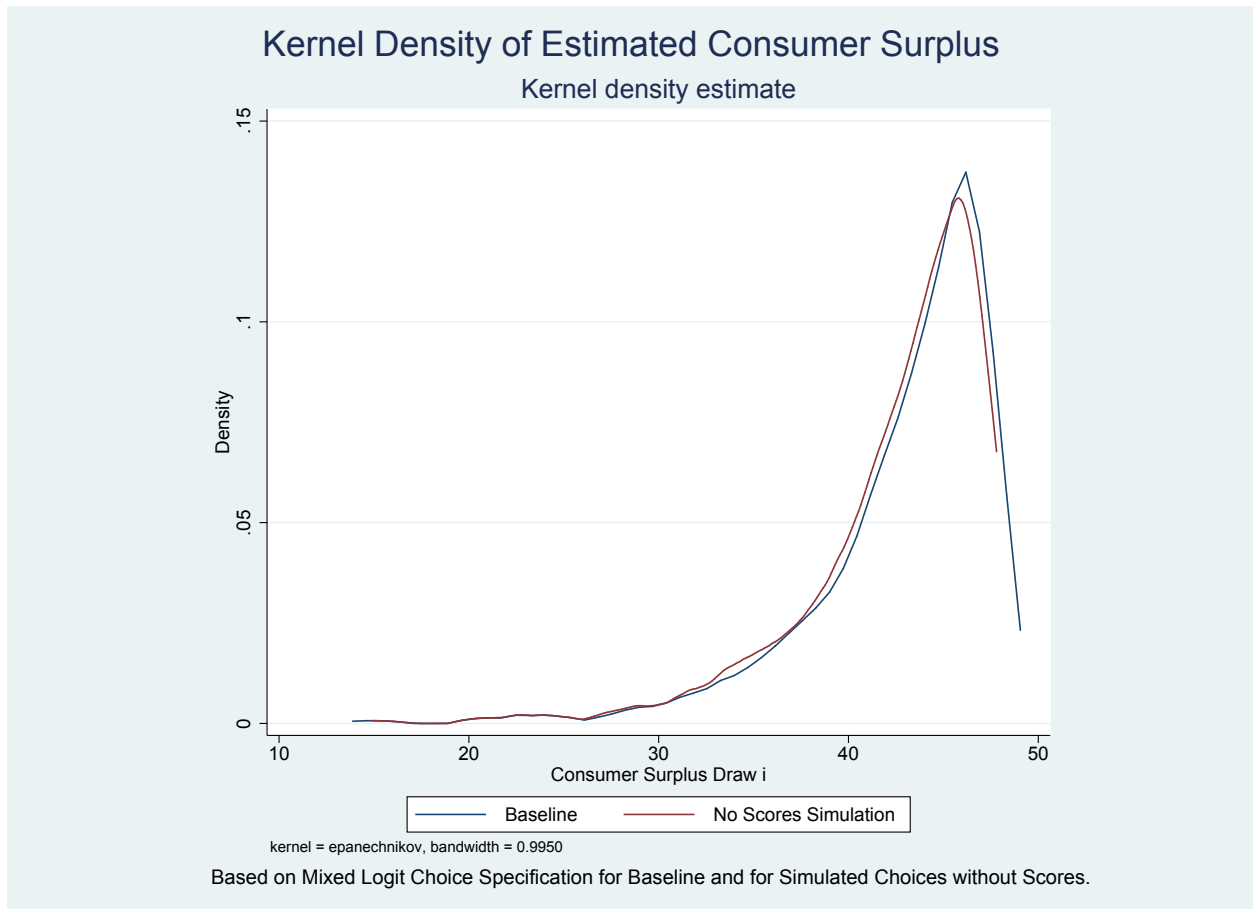
Note: This Figure displays jointly the kernel density estimates and the histograms of estimated product market shares in the baseline with scores and in the counterfactual scenario without scores. The Kolmogorov Smirnov test for equality of both distributions is rejected. Market shares/ choice Probabilities are based on the estimates in Table 4.

Figure 6: Estimated Inside Shares and Outside Option Shares With and Without Expert Opinion Scores



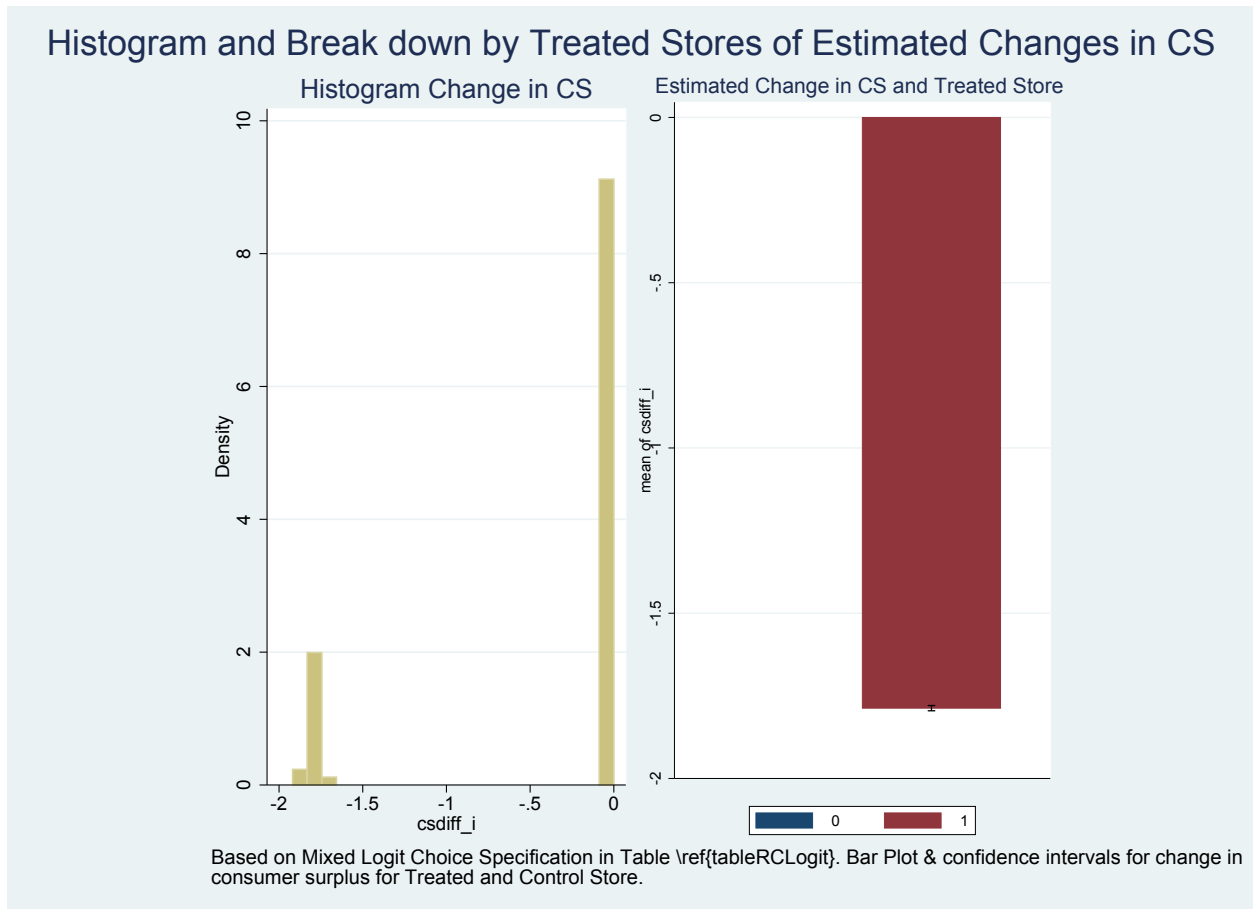
Note: This Figure displays the estimated market shares in the baseline with scores and in the counterfactual scenario without scores for the total wine inside options and for the outside option. Estimated Market shares (i.e., choice probabilities) are based on the estimates in Table 4.

Figure 7: Distribution of Estimated Consumer Surplus With and Without Expert Opinion Scores



Note: This Figure displays jointly the kernel density estimates of consumer surplus in the baseline with scores and in the counterfactual scenario without scores. The Kolmogorov Smirnov test for equality of both distributions is rejected. All estimates based on the demand estimates in Table 4.

Figure 8: Estimated Changes in Consumer Surplus With and Without Expert Opinion Scores



Note: In the left panel the change in consumer surplus density is displayed and then in the right panel, the break down of average change in CS (and confidence intervals) by treated (red) and control (blue) stores. All estimates based on the demand estimates in Table 4.