Analyzing Demand in the Spirits Market using the Random Coefficients Nested Logit model

by

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Abstract

We analyze demand in the spirits market, using two random coefficients logit models: BLP and RCNL. By estimation in PyBLP, we obtain the elasticities which inform policy makers about the efficacy of taxation of spirits. To perform the analysis, we make use of the Iowa Liquor Sales Dataset. We find mean own-price elasticities of -0.06 and -0.15 for the BLP and RCNL model respectively, which are on the lower end of the range found in the literature. These results show that demand for spirits is inelastic, and that therefore tax policies will at most have modest effects.

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Chapter 1

Introduction

Alcohol consumption in the United States is on the rise. Between 2002 and 2013, 12 month-prevalence of alcohol use in the United States rose from 65% to 72%, an increase of 11%. However, high-risk drinking, referring to men drinking five or more drinks a day and women drinking four or more drinks a day, increased far more with 30%. Problem drinking, defined as drinking alcohol to the point where it causes significant and repeated problems in life, increased by almost 50% (Grant et al., 2017).

There is overwhelming and widespread evidence for the hazardous effects of alcohol on human health. Alcohol has been found to be causally related to more than 60 different medical conditions. "Overall, 4% of the global burden of disease is attributable to alcohol, accounting for about as much death and disability globally as tobacco and hypertension" (Room et al., 2005). Some of the worst effects of alcohol are seen in cancers, HIV, tuberculosis and in particular liver disease (Kumar, 2017; Spillane et al., 2020). It is therefore no surprise that the increase in alcohol consumption has been accompanied by an increase in alcohol-related deaths. The number of alcohol induced deaths per 100,000 residents in the US rose from 14.4 in 2000 to 17.9 in 2016 among men, and from 4.1 to 6.6 among women (Spillane et al., 2020). In addition to the significant impact on human health, excessive alcohol consumption may also have profound effects on socio-economic variables. Numerous studies, e.g. De Silva et al. (2011) and Nyakutsikwa et al. (2021), have found that alcohol consumption exacerbates poverty, mostly because spending money on alcohol deprives people of the ability to use their wealth on productive resources. Moreover, the negative health impacts also come with a higher spending on health care costs. Alcohol also significantly contributes to both violent and property crime (Fergusson & Horwood, 2000).

With the overwhelming evidence for the social, economic and medical burden alcohol consumption places on society, numerous policies have been adopted by governments to address this problem. The two main instruments that governments have is to either (1) completely prohibit the consumption of alcohol or (2) implement regulatory measures in order to reduce demand for alcohol. The former option is the most direct attempt to reduce alcohol consumption, but has been found to lead to the introduction of black markets, smuggling and corruption (Kumar, 2017). Conveniently, the US itself provides a good example of the problems prohibition may lead to; between 1920 and 1933, the manufacture, transportation, storage and consumption of alcohol was forbidden. Although alcohol use initially fell, it subsequently saw a big increase. "Alcohol became more dangerous to consume; crime increased and became 'organized'; the court and prison systems were stretched to the breaking point; and corruption of public officials was rampant" (Thornton, 1991). Moreover, a full ban also raises ethical and judicial questions as it can be seen as a severe restriction of one's personal freedom to choose their own lifestyle.

It seems that therefore, regulation is the most realistic policy a government can pursue. Regulatory measures can take place in several different ways. One option is to let the government have a complete monopoly on sales of (a segment of) alcoholic beverages, as is the case in most Nordic countries. Alternatively, regulation agencies could restrict the hours of sale of alcohol in stores, which is also common in the Scandinavian countries. In Scotland and Ireland, the government has implemented a policy of 'minimum unit pricing'; a price floor that prohibits the sales of very cheap alcoholic beverages. Other measures include restrictions on advertising, discounts and the age at which alcohol can be bought. Perhaps the most straightforward policy a government can implement, is the introduction of a sales tax on alcohol with the intention to reduce its demand. This raises the question how effective such a policy is in practice. One of the key metrics in assessing the effectiveness of alcohol taxation is the concept of price elasticity of demand. Price elasticity measures the responsiveness of quantity demanded to changes in price. In the context of alcoholic beverages, it provides insights into how consumers adjust their consumption patterns when faced with price fluctuations. Investigating the price elasticity of demand for alcohol is essential for policymakers as it informs decisions related to tax rates and regulatory measures.

In this thesis, we investigate specifically the demand for distilled spirits. Spirits contain more alcohol than other beverages such as beer and wine, and are therefore considered to be 'harder'. Popular examples of spirits include whiskey, vodka and rum. Although these beverages are deeply entwined in American culture, it is precisely the large amount of alcohol that makes spirits even more dangerous than other alcoholic beverages. It is well-known that it takes spirits a much shorter amount of time to intoxicate a person than beer or wine. Spirits are also often taken in the form of shots, which leads to an intake of alcohol in just a few minutes, that would take hours to amount with beer. In addition, spirits consumers are also more likely than beer and wine consumers to consume larger-than-standard size drinks, also contributing to various health hazards (Klatsky et al., 2003). As soon as unrecorded alcohol consumption is taken into account, spirits consumption is the strongest determinant of adult male mortality rate, much stronger, for example, than tobacco and hard drugs consumption as well (Korotayev et al., 2018).

Our aim is to investigate how price and certain, potentially confounding, variables influence the demand of spirits. We make use of the Iowa Liquor Sales Dataset, a dataset that includes purchase information of spirits bought and sold in the US state of Iowa between 2012 and 2016. Iowa is a state that is fairly representative for multiple US States, especially those in the Midwest. The models we employ to perform the analysis are the BLP model by Berry et al. (1995) and the RCNL model by Grigolon and Verboven (2014). Both models fall into the class of random coefficients logit models, and have been widely applied in differentiated-product markets. The models are considered state-of-the-art in the field of industrial organization, as they allow for correlations between products that have more characteristics in common. This leads to more general substitution patterns, and therefore also more realistic own- and cross-price elasticities. In doing so, random coefficients logit models made a huge contribution to the field, as they significantly improved upon the existing models used in previous research in differentiated-product markets. The difference between RCNL and BLP is that in the former, products are divided into nests based on a certain categorization. The inclusion of a nesting structure allows for even more realistic substitution patterns. It is mainly relevant to industries where the product features that drive the substitution patterns are categorical in nature. The spirits market can be seen as such an industry, as it is fairly obvious to group the different products into nests based on the type of spirit (i.e. whiskey, vodka etc.). We will therefore mainly concentrate on the estimates found by using the RCNL model, with the BLP estimates being presented for comparison.

The objective of this thesis is two-fold. First of all, we wish to present evidence that should give further insight into the question what policies governments can implement in order to regulate the demand for spirits. The findings of the price elasticities ought to give a better picture of the efficacy of taxation on spirits in Iowa and the US, but may also be relevant to other similar countries. Second, due to the limited utilization of random coefficients logit models in previous papers examining demand in the alcohol and spirits industries, we wish to compare the findings of the RCNL model to those of the existing literature. Since the spirits market seems, at least on the surface, like an excellent framework to apply the RCNL model to, we hope that the nesting structure provides additional value.

The results we obtain from the analysis are unambiguous: we find mean own-price elasticities of -0.06 and -0.15 for the BLP and RCNL model respectively, indicating that demand for spirits is rather inelastic. Although the estimates are on the lower end, they are not inconsistent with earlier findings in the literature. The findings clearly point towards a conclusion that tax policies on spirits will likely only have moderate, but possibly still useful effects.

Chapter 2 of the thesis provides a literature review of the spirits market as well as previous findings for price elasticities for spirits and other alcoholic beverages. In Chapter 3, we present the dataset used and also discuss its shortcomings. This chapter also shows some descriptive statistics that give us some initial ideas about correlations between certain variables. Chapter 4 formally presents the models we use to perform the analysis, and also evaluates the appropriateness of some of the assumptions that are made in the context of our application. Finally in Chapter 5, we present the findings of the analysis and discuss the implications that the results have for future policies that governments may implement.

Chapter 2

Literature Review

In this section, we examine the existing body of literature concerning both demand analysis for spirits and other alcoholic beverages.

2.1 The spirits market

The global spirits market, characterized by its diverse nature, is a rapidly growing and evolving industry. "Over the past 50 years, the share of spirits in global alcohol production increased from around 30% to approximately 50%" (Cockx et al., 2021). According to the Distilled Spirits Council of The United States, spirits surpassed beer in market share in the US in 2022, obtaining a total share of 42.1% against 41.9% for beer.

The spirits market is segmented into many popular drinks such as whiskey, vodka and rum, with each their own unique characteristics. It is therefore not surprising that research indicates significant brand and product loyalty among consumers in this market: Dawes (2023) confirmed the results of previous industry reports showing that consumers report to stay with their preferred brands over extended periods of time. Figure 2.1 shows the top 5 best sold spirits in the US in 2022, according to the Distilled Spirits Council of the United States. Vodka has a long-standing tradition of being the most consumed spirit in the US, mainly due to it being a very versatile product; it can be used to mix with a wide variety of different flavors but can also be enjoyed on its own. It is also relatively cheap,

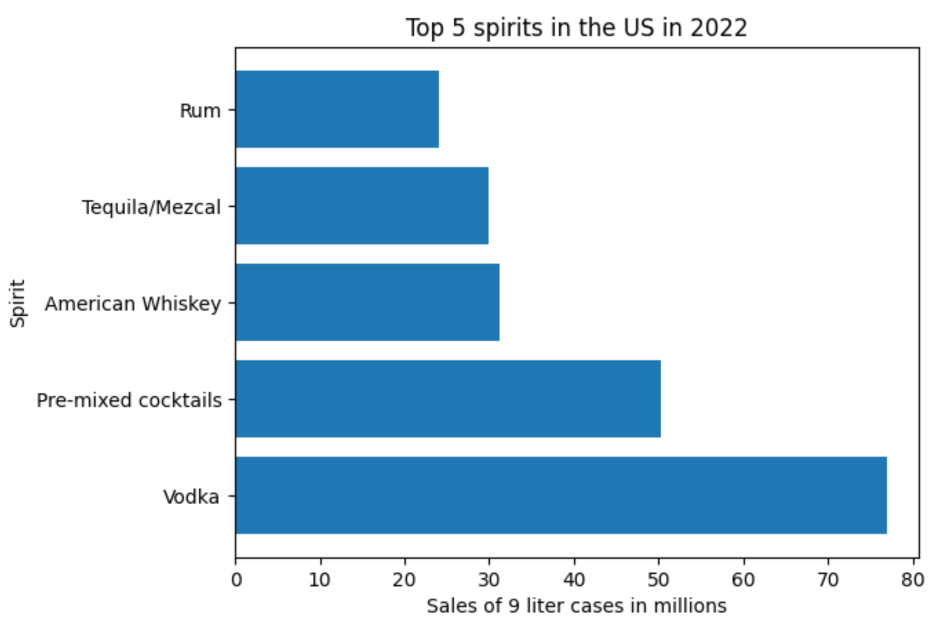


Figure 2.1: Top 5 best sold spirits in the US in 2022

compared to other spirits. American whiskey is deeply rooted into American culture, going back to the early arrival of the Europeans. It became popular because it did not need to be imported, as it could be distilled from domestically produced ingredients. Rum is the most steadily growing spirit in the United States, having built a reputation as a more premium choice compared to other spirits.

A recent development in the market is a growing preference by consumers for more luxury and exotic spirits: "At the global level, the volume of consumption of "standard" spirits (i.e., price per 75 cl bottle between $10 and $17) rose by only 1% per year between 2007 and 2017, the annual growth for "premium" (i.e., price per 75 cl bottle between $17 and $26) and "super-premium" (i.e., price per 75 cl bottle between $26 and $42) spirits was much higher: 2.6% and 3.3% respectively" (Cockx et al, 2019). Moreover, traditionally dominant local spirits have faded in popularity, in favor of foreign types. In France, for example, local spirits like Cognac, Armagnac and Calvados have made room for whiskey, rum and gin (Cockx et al., 2021).

2.2 Previous findings for demand in the alcohol and spirits market

There are numerous studies that have been done to analyze effects of price on demand for alcoholic beverages. As discussed in Gruenewald et al. (2006), increases in alcohol prices are consistently seen to reduce sales of alcoholic beverages, which is in accordance with basic economic theory. However, alcoholic beverages have also been demonstrated to be inelastic products, meaning that a 1% increase in price is associated with a less than 1% decrease in demand. Meta-analyses by both Gallet (2007) and Wagenaar et al. (2009) found, with some outliers present, that most studies show a price elasticity with absolute value smaller than one, with both reporting mean values of -0.5. Results vary more when only spirits are considered, with Gallet reporting a mean price elasticity of -1.09 and Wagenaar of -0.8. A literature review by Sousa (2014) of historical estimates of price elasticities for spirits in the UK after WW2, found a literature mean of -0.75. Gallet and Wagenaar both find spirits and wine to be consistently more elastic than beer, implying consumers are more influenced by price changes in the former two markets than in the latter. A time trend is also observable, with demand for alcohol becoming more elastic since approximately 1953 (Fogarty, 2010).

Fogarty (2010) found that demand for imported alcoholic beverages was more elastic than those that were manufactured domestically, which goes against the intuition that imported goods are less elastic due to their relatively higher price in general. Notably, Fogarty also observed that models which controlled for addiction as a variable were not greatly different from models that do not.

Most papers have adopted traditional linear or double-log specifications, although more recent ones have made use of functional forms like the Rotterdam model or the Almost Ideal Demand System (AIDS) (Gallet, 2007). Papers in which functional forms were used tend to produce smaller own-price elasticities than those in which standard linear models were applied (Gallet, 2007). Price elasiticities are most commonly constructed from demand models that are estimated using ordinary least squares (OLS). Other less-utilised estimation techniques include two stage least squares (2SLS), three stage least squares (3SLS), full information maximum likelihood (FIML), single equation maximum likelihood (MLE), generalised method of moments (GMM) and generalised least squares (GLS) (Gallet, 2007). Single-equation OLS estimates were more significantly different than estimates resulting from other approaches (Fogarty, 2010). On the other hand, "system-wide estimation approaches and pure time series approaches give estimates that are not statistically different from each other" (Fogarty, 2010).

Conlon and Gortmaker (2020) note that the spirits market is an excellent choice for analysis by means of the RCNL model, as the most important characteristics that drive the subsitution patterns are categorical. To the best of our knowledge, there currently exist two papers that apply the RCNL model to the spirits market: Miravete et al. (2020) and Conlon and Rao (2023). Both papers divide the spirits into nests based on the category they belong to: a nest for whiskeys, a nest for vodkas etc. In both papers, the elasticities that are found are much greater than the means in Gallet (2007), Wagenaar et al. (2009) and Fogarty (2010): -3.75 and -4.1 respectively.

Chapter 3

Data

3.1 The Iowa Liquor Sales Dataset

For our analysis, we make use of the Iowa Liquor Sales Dataset provided by the Iowa Department of Revenue.[1] The original dataset contains the spirits purchase information of Iowa Class E liquor licenses by product and date of purchase from January 1 2012 up until December 31 2017. Class E refers to the class of licenses which allows for the sales of beers, wines and spirits for off-the-premises consumption (meaning the beverages are not consumed at the place where it is sold), and are meant for commercial establishments (liquor stores, grocery stores, convenience stores etc.).

The Iowa Liquor Sales Dataset contains a total number of 12,591,076 sale records of 7395 different products across 416 cities in the state of Iowa. The total amount of stores in the dataset is 1884.[2] The map in figure 3.1 shows the distribution of the stores across the state. Each record includes the product, date, store, the amount of bottles of the corresponding product sold on that day by the store, retail price per bottle and the wholesale price per bottle, as well as the volume of the bottle.

3.2 Data cleaning

The dataset contains spirits with many different bottle volumes, ranging from bottles of 12 ml to bottle volumes of 2 litres. To prevent this from confusing the analysis, we have selected the most frequently sold volume which turned out to be 750 ml. All rows corresponding with products with a different bottle volume were dropped from the dataset, leaving a total of 5,629,548 sale records.

We have selected the 28 spirits that have been sold the most across both space and time. In doing so, we eliminate many beverages that only appear a limited amount of times in the dataset,

[1] Data are avaible at https://www.kaggle.com/datasets/residentmario/iowa-liquor-sales

[2] This includes different establishments of the same retailer. For example, the Hy Vee Food Store #2 in Iowa City is a different store than Hy Vee Food Store #3 in Waterloo

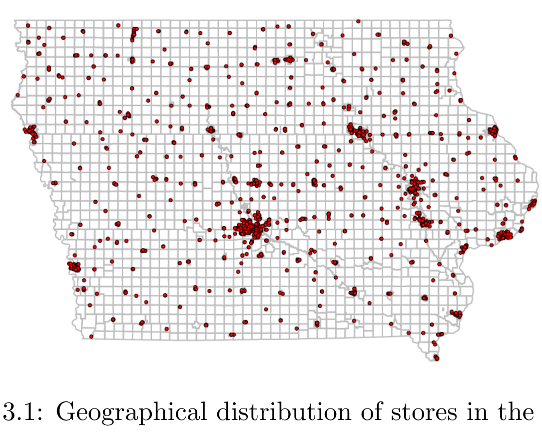


Figure 3.1: Geographical distribution of stores in the dataset

Category	# of products	Mean Share	Mean Price	Mean Wholesale Price
Whiskey	9	0.0094	16.02	11.15
Vodka	9	0.0101	10.71	7.25
Rum	5	0.0120	12.36	8.43
Other	5	0.0083	22.62	15.51
American	14	0.0130	12.78	8.71
Foreign	14	0.0092	16.89	11.67

Table 3.1: Means of market share, retail price and wholesale price by category

ensuring there is enough records of the selected products across all cities at every time. The selected products and their characeristics can be found in Appendix A. For similar reasons, we have selected the top 12 most frequently appearing cities in the dataset, leaving a total number of 593 stores in the cleaned dataset. Since we noticed significant discrepancies between the average total market share levels between the first quarter of 2012 and the third quarter of 2016 and those afterwards, we have decided to include only the first 19 quarters for our analysis.

We define a market as a unique combination of city and quarter. This gives a total number of $12 \cdot 19 = 228$ markets. Market shares were computed by taking the number of bottles of the product sold in that market, and dividing by the total number of bottles sold in that market. The price of product j in market t is defined as the weighted (by the market shares) average of the prices among the stores in the market. Wholesale prices were computed in a similar way.

In addition, we have gathered several product characteristics of the 28 products that we use. These characteristics are the alcohol percentage, the type of spirit (vodka, whiskey etc.) and the brand's country of origin. These features were found on the official websites of the brands. The set of products consists of nine whiskeys, nine vodkas, five rums and five spirits are classified as the 'other' category. These five beverages consist of two liquers, two tequilas and one cognac.

3.3 Shortcomings of the dataset

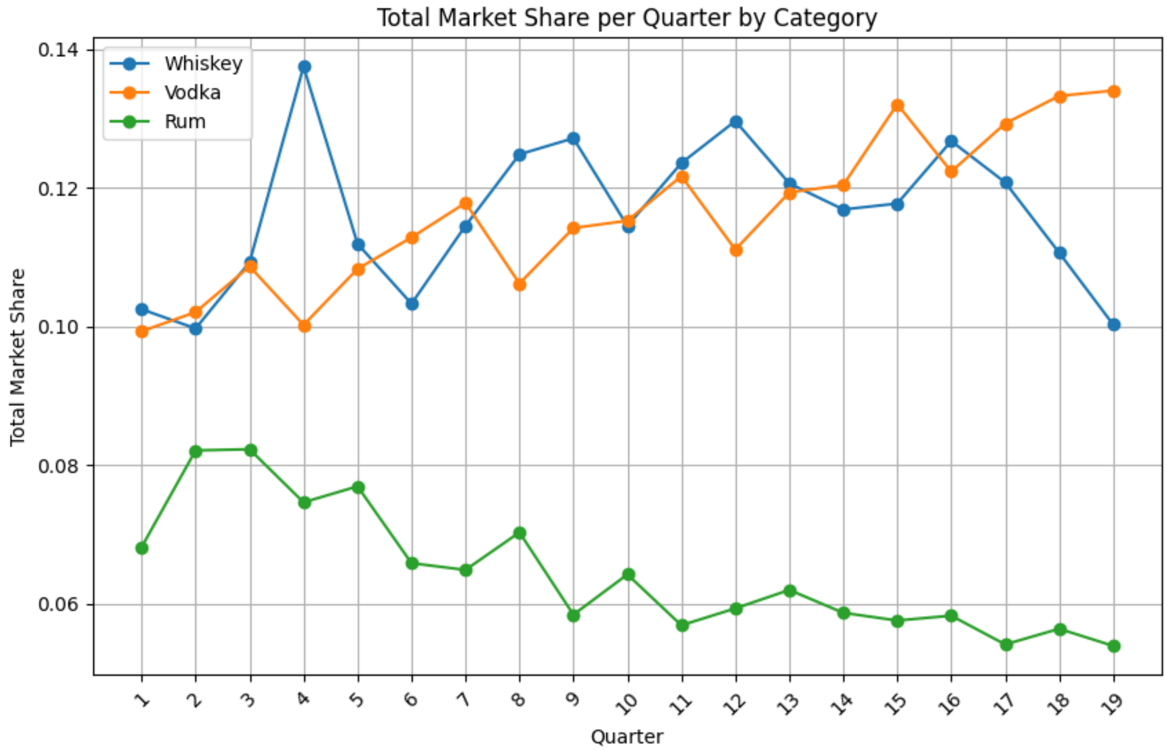
There are several problems in the dataset that need to be adressed.

First of all, there seems to be very limited variation across cities within both the retail prices and the wholesale prices. There is still clear variation over time, and this allows us to do proper analysis. However, the lack of geographical variation does have some implications for our model specification, as will be explained in section 4.7.

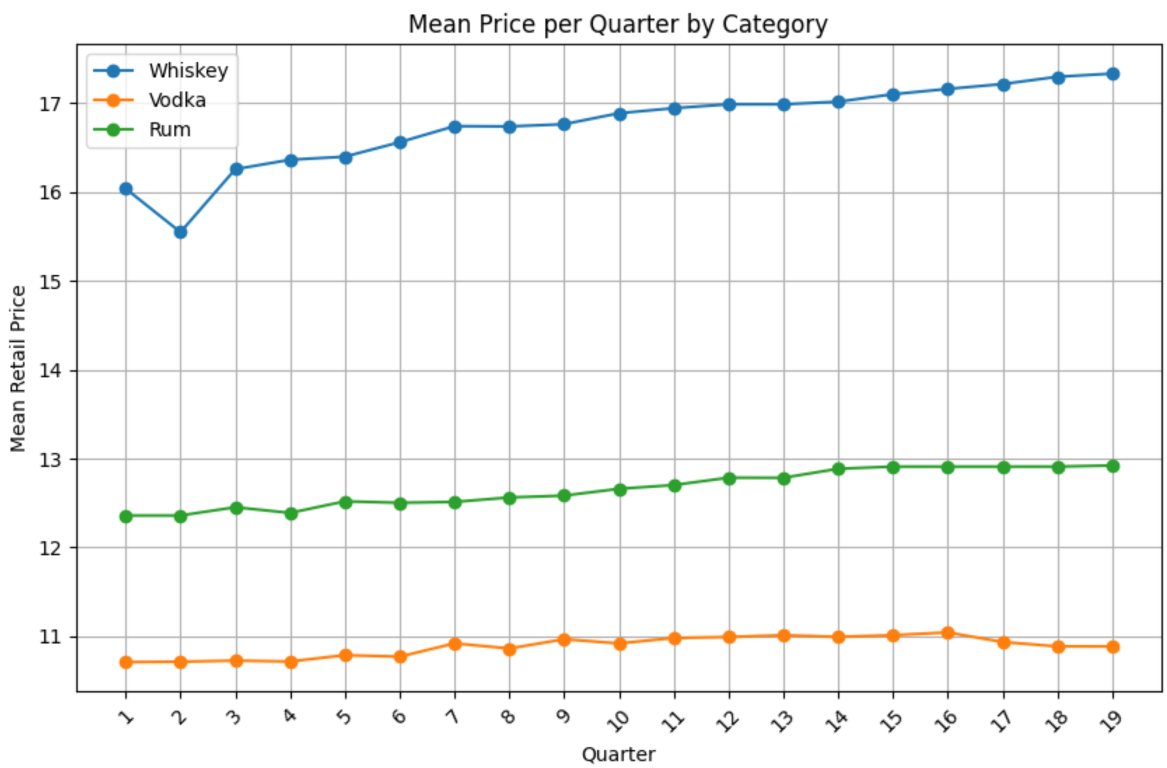
A second thing we observed is the extremely strong correlation between the retail prices and wholesale prices. For by far the largest group of records in the dataset, the wholesale price is approximately 50 % above the retail price. This has implications for the choice of instruments (see section 4.6), as we cannot have too much multicolinearity in our model.

3.4 Descriptive statistics

The 28 products used for our analysis can be categorized in several different ways. Table 3.1 shows summary statistics by type and origin respectively. We see that the products are relatively evenly divided among the different categories, although whiskey and vodka are slightly more represented compared to rum. American and foreign brands are split exactly 50/50 in our cleaned dataset. The table shows that the mean shares of the several types of spirits do not lie very far away from each other. Clearly prices of whiskey are higher than those of rum and vodka, with the latter's mean price suggesting a more competitive industry for that type of spirit. We can also note a higher mean retail price and wholesale price for foreign brands than American ones, which might very well be the result of the import costs.



(a) Total market share over time category



(b) Mean retail prices over time by category

Figure 3.2: Total shares and mean prices over time by category

Figure 3.2a and 3.2b show the total market share per quarter of each category (whiskey, vodka and rum) and their mean price per quarter respectively. We can see that whiskey and vodka dominate

	Coefficient	
Variable	Univariate Regression	Multivariate Regression
Alcohol	-0.1341 (0.2097)	-0.1982 (0.2035)
Whiskey	1.871 (3.1419)	-6.3201* (3.8412)
Vodka	-6.296* (2.920)	-12.1433* (4.0536)
Rum	-3.056* (1.719)	-11.6014** (4.7965)
American	-4.308* (2.438)	-1.3078 (2.7357)

Table 3.2: OLS regression results. Significance levels are indicated by * at the 10 % level, ** at the 5 % level and *** at the 1 % level.

the market, which is the result of the fact that there are simply more products of these categories in the dataset than rums. For all three categories we see a slow but steady rise in mean retail prices over time. Again, we clearly see that vodka is a cheaper product than whiskey, with rum finding itself somewhere in between.

We also perform a linear regression to observe the correlations between the prices and the product characteristics. Table 3.2 shows the estimation results when performing ordinary least squares regression of the mean retail prices on the product characteristics. The first column shows the estimated coefficients when regressing price on a single covariate, the second one shows the results when performing a joint regression. Interestingly, we see that alcohol percentage is negatively correlated with price, though both estimates are insignificant. It seems that stronger drinks are on average cheaper. We also see that whiskeys are positively correlated with prices in the univariate regression, but this picture changes when we evaluate the results of the multivariate regression: here the coefficient is significantly estimated to be negative. A possible explanation for this is that 5 of the 9 whiskeys in our dataset are foreign brands; we see that the estimate of the coefficient for the American variable is negative in both the uni- and multivariate regression. The coefficients for rum and vodka are significantly estimated to be negative in both regressions, which is consistent with the mean prices in table 3.1

From these descriptive statistics, a clear picture arises: whiskey is a more expensive product than vodka and rum which fall more into the cheaper categories. Foreign brands are also, on average, more expensive than American brands. These results are important, as they give an idea as to what factors might be confounding with price. Clearly there exist correlations between the product characteristics and the retail price that need to be taken into account. It is therefore essential that we control for these variables.

Chapter 4

Model

4.1 Introduction

The market for spirits is a differentiated-product market, meaning that the products sold are distinct from each other in terms of quality, features, branding and other possible characteristics. Nevo (2000) identifies several key problems that are associated with demand estimation in this type of market. The first one is a so-called 'dimensionality problem'; for markets with a reasonable amount of products the amount of parameters to estimate becomes very large very quickly.[1] The second problem is the heterogeneity in consumer tastes; we cannot assume that all consumers have identical preferences. Moreover, it is well known that prices are endogenous variables which - if this is not taken into account - leads to upward sloping demand curves.

The logit demand model by McFadden (1973) presents a structural approach to estimation in differentiated-product markets. He developed a framework, in which indirect utility is modeled as a linear function of price, product characteristics and an unobserved error term:

$$u_{ijt} = \gamma + \alpha p_{jt} + x'_{jt}\beta + \xi_{jt} + \epsilon_{ijt} \tag{4.1}$$

Here γ denotes the intercept, p_{jt} is the price of product j in market t, x_{jt} is a K-dimensional vector of product characteristics observed by the econometrician, ξ_{jt} are the product characteristics observed by the consumer and firms but unobserved by the econometrician and ϵ_{ijt} are the idiosyncratic taste shocks.

The logit model solves the dimensionality problem, but relies on strong assumptions: "due to the restrictive way in which heterogeneity is modeled, substitution between products is driven completely by market shares and not by how similar the products are" (Nevo, 2000), i.e. the own- and cross-price elasticities produced by the model are not in any way influenced by product characteristics and therefore not very realistic. This can be seen in the the parameters for price and the product characteristics; they are assumed to be constant across consumers.

Berry (1994) was the first to address all of the problems mentioned above, by introducing an approach to demand estimation in which both heterogeneity among consumers as well as different product characteristics are taken into account, using only market-level data. He also formulated an equation for indirect utility, similar to McFadden's:

$$u_{ijt} = \gamma + \alpha_i p_{jt} + x'_{jt}\beta_i + \xi_{jt} + \epsilon_{ijt} \tag{4.2}$$

[1] Consider, for example, the popular constant elasticity framework:

$$\ln q_j = \alpha_j + \sum_k \eta_{jk} \ln p_{jk} + \epsilon_j$$

where η_{jk} represents the elasticity of product j with respect to product k.

Applying this framework to an industry with K products, gives K^2 elasticity parameters to estimate. For reasonably sized markets, this number becomes very large.

In this formulation, however, parameters for price and product characteristics are, unlike the standard logit model, allowed to vary across consumers. Key to this framework is the assumption that a consumer makes a discrete choice: they choose to buy only one product out of all the available options in the market. By making distributional assumptions on the taste shocks ϵ_{ijt}, Berry obtained an expression for the choice probabilities of the products, which can be interpreted as market shares, which can obviously be observed from data. This set the stage for a formal estimation procedure, introduced in the groundbreaking paper by Berry, Levinsohn and Pakes, hereafter Berry et al. (1995) (in short 'BLP').

The BLP method revolutionized demand estimation in differentiated-product markets. It built upon Berry's framework by providing a systematic method for estimating the model parameters. At the core of this method is the use of a nested fixed-point algorithm, in order to numerically solve the set of complex non-linear equations that arises in the Berry framework. After this, we are simply left with a standard regression equation. Notably, BLP adresses the endogeneity of prices, by making use of instrumental variables. The method produces own- and cross-price elasticities that are far more realistic, since subtitution patterns are not merely driven by market shares but also by product similarity.

In his 1994 paper, Berry also considers a special case of his framework, the so-called nested logit model. In this model, parameters are assumed to be constant across consumers, similar to McFadden's logit model. In addition however, products are grouped into nests, based on a certain characteristic. For example, in the context of our spirits market, products might be grouped into the nest whiskey, vodka and rum, or into an American and non-American brand nest. The inclusion of nests is accounted for in the equation for indirect utility:

$$u_{ijt} = \gamma + \alpha p_{jt} + x'_{jt}\beta + \xi_{jt} + \zeta_{igt} + (1-\rho)\epsilon_{ijt} \tag{4.3}$$

where product j belongs to nest g and $\rho \in [0, 1)$

We can see that the idiosyncratic taste shock now also contains the term ζ_{igt} , which accounts for the taste shock that happens to the nest that product j belongs to. This allows for correlation between products based on similarity, albeit in a more restricted manner than in the later BLP method, producing more reasonable substitution patterns. If a product in nest A is increased in price, this will have a more profound effect on the demand for other products in nest A than on products in other nests, since consumers are realistically more likely to switch to a similar product. However, since taste parameters are not allowed to vary across consumers, the nested logit model still faces the problem that substitution between products within nests and substitution between the nests themselves are only driven by market shares.

Grigolon and Verboven (2014) combine the nested logit model and the BLP model, with their random coefficients nested logit (RCNL) model. Although BLP accounts for heterogeneity in taste preferences among consumers, it still assumes that idiosyncratic taste shocks to the indirect utility are i.i.d. across products. RCNL deals with this problem by, just like in the nested logit model, grouping the products into nests and including a group-specific component in the error term, while maintaining the advantages of BLP:

$$u_{ijt} = \gamma + \alpha_i p_{jt} + x'_{jt}\beta_i + \xi_{jt} + \zeta_{igt} + (1-\rho)\epsilon_{ijt} \tag{4.4}$$

with again $\rho \in [0, 1)$

This model is particulary popular in applications where the most important set of characteristics that determine the substitution is categorical (Conlon & Gortmaker, 2020). As described in Chapter 2, the spirits market can be seen as such a market.

We will first formulate the BLP model, which can be seen as a special case of the RCNL model. We then formulate the RCNL model, which is followed by an outline of the nested fixed-point algorithm.

The nested-fixed point algorithm leads to the construction of a regression equation, which will be estimated by means of the instrumental variables (IV) technique.

4.2 BLP Model

The demand system we introduce here is based on the utility framework from Berry (1994) and Berry et al. (1995). Assume that there are T markets with market t having J_t products. Assume there is a mass of M_t consumers in market t. The utility that consumer i experiences as a result of the consumption of product j in market t is given by:

$$u_{ijt} = \gamma + \alpha_i p_{jt} + x'_{jt}\beta + \xi_{jt} + \epsilon_{ijt} \tag{4.5}$$

Again, γ denotes the intercept, p_{jt} is the price of product j in market t, x_{jt} is a K-dimensional vector of product characteristics observed by the econometrician, ξ_{jt} are the product characteristics observed by the consumer and firms but unobserved by the econometrician and ϵ_{ijt} are the idiosyncatic taste shocks. We assume that ϵ_{ijt} follows an i.i.d. type 1 Extreme Value distribution.

This is a slightly modified version of the original utility equation in Berry et al. (1995), which will be explained in 4.7.

We assume that α_i follows an i.i.d. normal distribution:

$$\alpha_i \underset{\text{i.i.d.}}{\sim} N(\alpha, \sigma_p) \tag{4.6}$$

This allows us to write:

$$\alpha_i = \alpha + \sigma_p \nu_i \tag{4.7}$$

with $\nu_i \sim N(0, 1)$

Equation (4.5) can then be rewritten as:

$$\begin{aligned} u_{ijt} &= \gamma + (\alpha + \sigma_p)p_{jt} + x'_{jt}\beta + \xi_{jt} + \epsilon_{ijt} \\ &= \underbrace{\gamma + \alpha p_{jt} + x'_{jt}\beta + \xi_{jt}}_{\equiv \delta_{jt}} + \underbrace{\sigma_p \nu_i p_{jt} + \epsilon_{ijt}}_{\equiv \mu_{ijt}} \\ &= \delta_{jt} + \mu_{ijt} \end{aligned}$$

δ_{jt} is the mean utility of product j in market t, whereas μ_{ijt} is the random, idiosyncratic component of utility.

In addition, there is also an outside option with utility given by:

$$u_{i0t} = \epsilon_{i0t}$$

The outside option represents the choice where the consumer decides not to buy any products in market t.

We assume that the consumer makes a discrete choice:

$$d_{ijt} = \begin{cases} 1 & \text{if } u_{ijt} \geq u_{ij't} \forall j' \in J_t \cup \{0\} \\ 0 & \text{otherwise} \end{cases} \tag{4.8}$$

$d_{ijt} = 1$ represents the choice where consumer i buys product j in market t.

Using the distribution of ϵ_{ijt}, the probability of consumer i buying product j in market t, i.e. the market share of product j in market t, is given by:

$$s_{jt}(\boldsymbol{\delta}_t, \theta) = \int \frac{\exp(\delta_{jt} + \sigma_p \nu_i p_{jt})}{\sum_{j \in J_t \cup \{0\}} \exp(\delta_{jt} + \sigma_p \nu_i p_{jt})} f(\nu_{it}, \sigma_p) d\nu_{it} \tag{4.9}$$

.

This is often referred to as *mixed logit*, since an invidiual i's demand is given by a multinomial logit kernel where $f(\nu_{it}, \sigma_p)$ denotes the joint distribution over the heterogenous individuals i (Conlon & Gortmaker, 2020).

4.3 RCNL Model

Grigolon and Verboven (2014) extend the BLP model with the inclusion of a nesting structure.

Let again T denote the set of markets, M_t be the mass of consumers in market t, and J_t be the set of products in market t. Let G_t be the set of all nests within market t.

Consumer's i utility from product j in nest g, in market t is then given by:

$$u_{ijt} = \gamma + \alpha_i p_{jt} + x'_{jt}\beta + \xi_{jt} + \zeta_{igt} + (1-\rho)\epsilon_{ijt} \tag{4.10}$$

where $\rho \in [0, 1)$

The outside good has its own nest $g = 0$ and its utility is now given by:

$$u_{i0t} = \zeta_{i0t} + (1-\rho)\epsilon_{i0t} \tag{4.11}$$

The dissimilarity parameter ρ quantifies how much consumers differentiate between the products within a nest. Note that if ρ goes to 1, the product-dependent part of the idiosyncratic taste shock (ϵ_{ijt}) becomes negligible, indicating that consumers perceive the products within nest g as perfect substitutes. If $\rho = 0$, we obtain the BLP model. Hence BLP can be seen as a special case of RCNL.

If we assume that $\zeta_{igt} + (1-\rho)\epsilon_{ijt}$ follows an extreme value distribution and if we again assume that α_i follows an i.i.d. $N(\alpha, \sigma_p)$ distribution, the market shares are given by:

$$s_{jt}(\boldsymbol{\delta}_t, \sigma_p) = \int \pi_{jt}(\boldsymbol{\delta}_t, \sigma_p) f(\nu_{it}, \sigma_p) d\nu_{it} \tag{4.12}$$

.

where:

$$\pi_{jt} = \frac{\exp((\delta_{jt} + p_{jt}\sigma_p\nu_i)/(1-\rho))}{\exp(I_{ig}/(1-\rho))} \frac{\exp I_{ig}}{\exp I_i} \tag{4.13}$$

where I_{ig} and I_i are McFadden's (1978) inclusive values with:

$$I_{ig} = (1-\rho)\ln\sum_{m=1}^{J_g}\exp((\delta_{mt} + p_{jt}\sigma_p\nu_i)/(1-\rho))$$

and:

$$I_i = \ln(1+\sum_{g=1}^{G}\exp I_{ig})$$

with J_g the set of products in nest g.

4.4 Estimation approach

Equation 4.12 denotes the market shares being expressed as a function of the mean utilities $\boldsymbol{\delta}_t$. We can write:

$$\boldsymbol{s}_t \equiv F_t(\boldsymbol{\delta}_t, \sigma_p) \tag{4.14}$$

We now arrive at the key finding of Berry (1994): the equations in 4.14 must hold exactly at the true values of $\boldsymbol{\delta}_t$ and $\boldsymbol{S}_t$, which we denote the vector of market shares s_{jt} in market t. Then, conditional on the true values of $\boldsymbol{\delta}_t$ and given the density of the random part ν_i as well as some weak regularity conditions, there exists a unique mean utility vector $\boldsymbol{\delta}_t^*$ such that equations 4.14 hold for the observed market shares $\boldsymbol{S}_t^*$. In other words:

$$\boldsymbol{\delta}_t^* \equiv F_t^{-1}(\boldsymbol{S}_t^*, \sigma_p) \tag{4.15}$$

[2]

Remember that $\delta_{jt} = \gamma + \alpha p_{jt} + x_{jt}'\beta + \xi_{jt}$. We can use this in combination with the unique mean utility vector $\boldsymbol{\delta}_t^*$ to construct a regression equation:

$$\delta_{jt}^* = \gamma + \alpha p_{jt} + x_{jt}'\beta + \xi_{jt} \tag{4.16}$$

The question arises: how do we obtain $\boldsymbol{\delta}_t^*$? The nested-fixed point algorithm by Berry et al. (1995) numerically solves 4.14.

Define:

$$\begin{aligned}\boldsymbol{\theta}_1 &= (\gamma, \alpha, \beta)\\ \boldsymbol{\theta}_2 &= (\sigma_p, \rho)\end{aligned} \tag{4.17}$$

Let us begin with an initial guess of $\boldsymbol{\delta} = (\boldsymbol{\delta}_1, \boldsymbol{\delta}_2, ..., \boldsymbol{\delta}_T)$: $\boldsymbol{\delta}^{k=0}$. A good initial guess is to set $\boldsymbol{\delta}^{k=0} = 0$. We also make an initial guess for ρ. Assume for a moment that we know the value of σ_p. Using the density of ν_i we can approximate the integral in 4.12, by using some numerical integration technique. In the original BLP paper, this numerical integration technique was to use Monte Carlo

[2]In his 1994 paper, Berry proves that the function F is one-to-one.

simulations drawn from the density of $\boldsymbol{\mu}_{it}$. In recent years, other methods have seen an increase in popularity, such as antithetic draws, Halton draws and, which is the method that we will apply, Gauss-Hermite quadrature:

$$s_{jt}(\boldsymbol{\delta}_t, \sigma_p) \approx \sum_{h=1}^{H} \frac{w_h}{\sqrt{\pi}} \frac{\exp((\delta_{jt} + \sqrt{2} z_h p_{jt} \sigma_p)/(1-\rho))}{\exp(\hat{I}_{ig}/(1-\rho))} \frac{\exp \hat{I}_{ig}}{\exp \hat{I}_i} \tag{4.18}$$

with

$$\hat{I}_{ig} = (1-\rho) \ln \sum_{m=1}^{J_g} \exp((\delta_{mt} + \sqrt{2} z_h p_{jt} \sigma_p)/(1-\rho))$$

and:

$$\hat{I}_i = \ln(1 + \sum_{g=1}^{G} \exp \hat{I}_{ig})$$

where w_h and z_h are the weights and nodes respectively.

The next step is to update our guess of $\boldsymbol{\delta}$ according to:

$$\delta_{jt}^{k+1} = \delta_{jt}^{k} + \ln s_{jt} - (1-\rho) \ln(s_{jt}(\delta_t^k, \sigma_p)) \tag{4.19}$$

As shown by Brenkers and Verboven (2006), 4.19 is a contraction mapping, and is therefore guaranteed to converge. We update the value of $\boldsymbol{\delta}^k$ until $|\ln s_{jt} - (1-\rho)\ln(s_{jt}(\delta_t^k, \sigma_p))| < \epsilon_{\text{tol}}$, with ϵ_{tol} the tolerance level (which is always an extremely small value, e.g. $10e^{-12}$). After the final update, we obtain our approximate $\boldsymbol{\delta}^*$, and can perform regression.

Let $\boldsymbol{X} = (\mathbf{1}, \boldsymbol{p}, \boldsymbol{x}_1, ..., \boldsymbol{x}_K)$. Due to the endogeneity of prices, we also construct P instruments for this variable. Let $\boldsymbol{Z}$ be the matrix of exogenous variables: $\boldsymbol{Z} = (\mathbf{1}, \boldsymbol{x}_1, ..., \boldsymbol{x}_K, \boldsymbol{z}_1, ..., \boldsymbol{z}_P)$. These variables are correlated with the mean utility, only through the prices and so are uncorrelated with the error term $\boldsymbol{\xi} = (\xi_{11}, ..., \xi_{J_1 1}, ..., \xi_{1T}, ..., \xi_{J_T T})$. Therefore, the population moments (at the true values of σ_p and ρ) are:

$$\mathbb{E}[\boldsymbol{Z'}\boldsymbol{\xi}(\hat{\boldsymbol{\theta}}_2)] = 0 \tag{4.20}$$

We can then construct the GMM estimator, to estimate the parameters in 4.16:

$$\hat{\boldsymbol{\theta}}_1 \equiv \widehat{\begin{pmatrix} \gamma \\ \alpha \\ \beta \end{pmatrix}} = (\boldsymbol{X'ZWZ'X})^{-1}\boldsymbol{X'ZWX'}\boldsymbol{\delta} \tag{4.21}$$

Here we set the weighting matrix $\boldsymbol{W} = (\boldsymbol{Z'Z})^{-1}$

Remember that thus far we have assumed to know the values of the parameters in $\boldsymbol{\theta}_2$, but we obviously do not. We will now search over these parameters, σ_p and ρ. Using our estimated parameters, we can compute the regression residuals $\hat{\boldsymbol{\xi}}$:

$$\hat{\boldsymbol{\xi}} = \boldsymbol{\delta} - \boldsymbol{X}(\boldsymbol{X'ZWZ'X})^{-1}\boldsymbol{X'ZWX'}\boldsymbol{\delta} \tag{4.22}$$

Our problem is now reduced to finding the best estimator $\hat{\boldsymbol{\theta}}_2$ that fits the sample analogue of the moment conditions in 4.20:

$$\hat{\boldsymbol{\theta}}_2 = \underset{\boldsymbol{\theta}_2}{\operatorname{argmin}}[\boldsymbol{Z'}\hat{\boldsymbol{\xi}}(\boldsymbol{\theta}_2)]'\boldsymbol{W}^{-1}[\boldsymbol{Z'}\hat{\boldsymbol{\xi}}(\boldsymbol{\theta}_2)] \tag{4.23}$$

4.5 Elasticities

One of the most interesting results we can get from applying the BLP or RCNL model are the own- and cross-price elasticities. The elasticity of product j with respect to product k in market t is given by:

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} \tag{4.24}$$

If $j = k$, we have an own-price elasticity, otherwise a cross-price elasticity. The own-price elasticity gives the percentage change in demand of a product in response to a 1 % increase in price. This means that an elasticity of -1.5 implies that a 10 % increase in price, reduced demand by 15 %. Cross-price elasticities tell how the demand of a product changes in response to a price increase of a competing product. While own-price elasticities are almost always negative, typically cross-price elasticities have positive values. We would expect that the more similar a product is, the larger the cross-price elasticity.

In addition we can also obtain the so-called diversion ratios, given by:

$$\Upsilon_{jkt} = -\frac{\partial s_{kt}}{\partial p_{jt}} / \frac{\partial s_{jt}}{\partial p_{jt}} \tag{4.25}$$

The diversion ratio of product j with respect to product k in market t indicates the fraction of consumers who leave product j for product k given a price increase of product j. In more plain terms: it is the ratio of switchers to leavers. Diversion ratios can be very informative, as they can be seen as a measure of the level of competition in the market. In particular, the diversion ratio to the outside good informs us about the substitution effect present in the industry.

Finally, we also consider the aggregate elasticity:

$$E_t = \sum_{j \in J_t} \frac{s_{jt}(p_{jt} + \phi p_{jt} - s_{jt})}{\phi} \tag{4.26}$$

with ϕ a scalar factor.

This reflects the change of total demand for the market with respect to the introduction of a sales tax of some factor ϕ.

4.6 Instruments

As said earlier, to address the correlation between prices and the unobserved product characteristics, we need to find suitable instruments.

The traditional BLP approach is to define the instruments as the sum of characteristics of all competing products. The idea behind these 'BLP instruments' is that products with closer substitutes have a lower mark-up, meaning they also have lower prices, in comparison with products that are less competitive. A problem with this approach for our spirits market is that, as discussed in Chapter 3, products characteristics do not vary over time and space. The consequence of this is that we cannot use competing product characteristics as instruments, since these will be perfectly colinear with the product characteristics variables in x_{jt}, which makes estimation infeasible. For this reason, we make use of two alternative instruments: Hausman instruments, and an instrument based on the wholesale price. Let z_1 and z_2 denote the Hausman instrument and 'wholesale instrument' respectively, and let ω_{jt} denote the wholesale price of product j in market t. The instruments are defined as:

$$\begin{aligned} z_{1jt} &= \overline{p}_{jq} - p_{jt} \\ z_{2jt} &= 1.5\omega_{jt} - p_{jt} \end{aligned} \tag{4.27}$$

Here $\overline{p}_{jq}$ denotes the mean of the price of product j across all markets in quarter q, where market t belongs to quarter q. The Hausman instrument, introduced by Hausman (1996) takes the difference between this mean and the price of the product in market t itself. The idea behind the Hausman instrument is that prices in past and future markets are correlated with the cost, and thus the price of the product, while being independent of demand shocks in the current market.

The second instrument we use is based on the wholesale price. Again, this instrument came about due to shortcomings in the dataset. As explained in Chapter 3, the retail price is in most cases approximately 50% above the wholesale price, meaning that the use of this instrument would lead to extremely high multicolinearity. Although, we obviously need to satisfy the relevance condition ($\text{Cov}(p_{jt}, z_{2jt}) \neq 0$), the correlation cannot be too high. We therefore construct, somewhat artificially, a modified instrument which is still based on the discrepancy between prices and wholesale prices. The second instrument in 4.27 was found to have only a 0.08 correlation with prices, and is therefore a suitable choice.

4.7 Suitability of the model

As with any model, it is crucial that we evaluate the appropriateness of the assumptions that are made in relation to the market that we analyze.

First of all, the reader may notice that in our model only the coefficient on price α_i is allowed to vary across consumers; the taste parameters for the product characteristics β are assumed to be constant across all consumers. This can indeed be seen as somewhat of a shortcoming of the model - after all it is precisely the preferences for product features that one would expect to have a lot of heterogeneity, likely more than the prices. Although we acknowledge that allowing for individual-specific β_i-parameters could potentially capture more nuanced variation in consumer preferences, practical considerations such as model complexity and computational feasibility led to the decision to fix the parameters. Moreover, we do account for correlations between spirits of the same type with the inclusion of the nesting structure in the RCNL model; substitution patterns will therefore still be driven by product similarity and not just by market shares.

Another assumption that requires some additional explanation, is that of the discrete choice made by the consumer, as stated in 4.8. One might rightfully ask the question whether such an assumption is appropriate for the spirits industry, since a consumer might very well buy more than one bottle once he is in a retail store. It is important to verify whether this assumption is realistic, as otherwise the model might overstate the own-price elasticities (Miravete et al., 2020). Miravete et al. (2020) test for so-called 'stockpiling' in the spirits market, i.e. the act of buying many products at once, and find no evidence for this. Although this obviously does not prove that the market can be perfectly captured by a discrete-choice model, it is evidence that the model is a good approximation of the market.

Finally, it is worth mentioning that it would also be possible to include a product-fixed effect term in the equation for indirect utility. However, given the lack of variation across cities, we have chosen not to do this.

Chapter 5

Empirical Analysis

5.1 Preparation with PyBLP

To estimate our results, we make use of the PyBLP module in Python, developed by Conlon and Gortmaker (2020). To make our dataset compatible with the PyBLP format, we structure our variables in a very specific way illustrated in the code that can be found in Appendix B.

In our model formulation, we include the variables 'price', 'alcohol' and the dummy variables 'whiskey', 'vodka', 'rum', and 'american' for employing the BLP model. For RCNL we include only 'price', 'alcohol' and 'american', as the nests that we define are 'whiskey', 'vodka', 'rum' and 'other' (indicating the five beverages that belong to categories of which there are too limited observations). We make use of the BFGS optimization algorithm.

5.2 Results

Table 5.1 shows the estimation results of the parameters for both the BLP and RCNL model.

The estimate of the coefficient for price is negative in both models, meaning that increase in price causes disutility, consistent with basic intuition. In the BLP model, a price increase of 1 dollar causes on average a decrease utility of 0.0081 ceteris paribus, whereas in the RCNL model this number is 0.0092. The coefficient for price in the BLP model is not statistically significant at any conventional level, unlike the RCNL estimate which is significant at the 1 % level.

The estimated standard deviation σ_p is 0.017 for BLP and only 0.000012 in the RCNL model, expectedly indicating not much heterogeneity among consumers for price preferences - people generally like lower prices. A possible explanation for the extremely low value of σ_p in, in particular, the RCNL model might be the lack of variation across prices in the dataset. Note that in both models the estimates for the standard deviation are not statistically significant at any level.

Estimates for the taste parameters of the product characteristics are all statistically significant at some level. Notably, all three included categories - whiskey, vodka and rum - have positive estimates, indicating that people particularly like these types of spirits, as opposed to other categories.

In the RCNL model, the estimates for coefficients for the alcohol and in particular the American parameter are smaller than the BLP estimates.

Both the BLP and RCNL estimates of the model intercepts are negative and statistically significant. The interpretation is that, on average, people do not like a free bottle of a spirit with no alcohol that is not a whiskey, vodka or rum, and not American. Such a product is obviously purely hypothetical, and none of the products in the dataset remotely resemble this. Therefore we should not place too much emphasis on the interpretation of the intercepts.

The dissimilarity parameter ρ is insignificantly estimated to be 0.2, which is on the somewhat lower end compared to the estimate in Conlon and Rao (2023), which found a value of 0.423 (0.026). The low value indicates that consumers still value the spirits within a category for their own unique features, and not just for the fact that they belong to that category. In other words, the nest effect is relatively marginal.

	BLP	**RCNL**
Linear parameters		
Variable	Coefficient	Coefficient
Price	-0.0081	-0.0092***
Alcohol	0.013***	0.0085***
Whiskey	0.14*	
Vodka	0.17***	
Rum	0.31***	
American	0.038**	0.0067*
Constant	-4.8***	-4.4***
Non-linear parameters		
σ_p	0.017	0.000012
ρ		0.2
Elasticities		
Own-price elasticity	-0.06	-0.14
Diversion ratio to outside good	0.817	0.666
Aggregate elasticity	-0.017	-0.029

Table 5.1: Estimation results using the BLP and RCNL model. Significance levels are indicated by * at the 10 % level, ** at the 5 % level and *** at the 1 % level.

The mean own-price elasticities of the spirits are on the lower end in both the BLP and RCNL model, although the RCNL estimate of -0.14 is within the range found in the literature unlike the BLP elasticity of 0.06 which is slightly lower than what is commonly found in the literature. The discrepancy between the two, although not extremely large, might very well be the result of the more realistic substitution patterns generated by the nesting structure in the RCNL model.

Consistent with the low value of the own-price elasticity, are the findings of the cross-price elasticities. Table 5.2 presents the mean cross-price elasticities found by the RCNL model for each category, between both (1) the other products within the same category and (2) all the other products not in the same category. For example, whiskeys have on average a cross-price elasticity of 0.0015 with other whiskeys, and a cross-price elasticity of 0.0011 with other spirits. Although the discrepancy is again

Category	With own category	With other spirits
Whiskey	0.0015	0.0011
Vodka	0.0017	0.0008
Rum	0.0015	0.0013
American	0.0013	0.0012
Foreign	0.0016	0.0011

Table 5.2: Mean cross-price elasticities by category found in the RCNL model

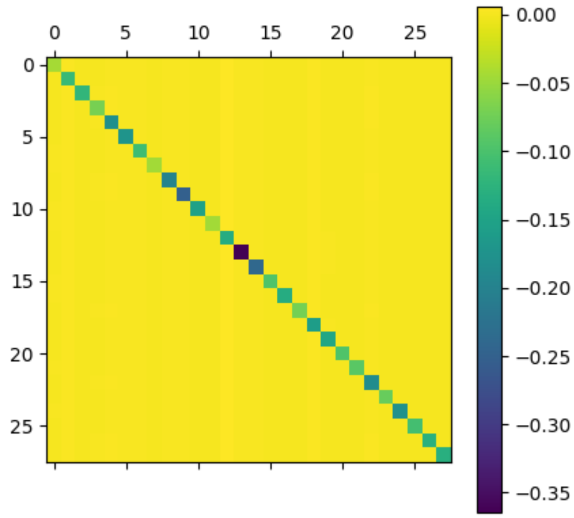


Figure 5.1: Own- and cross price elasticities of a sample market. Diagonal indicates the own-price elasticities.

minor, the fact that we observe higher mean cross-price elasticities between spirits of the same type than between spirits of different types can likely be explained by the substitution patterns generated by the nesting structure in RCNL. After all, the estimate for the dissimilarity parameter ρ is small but not zero. It is consistent with the idea that if a product increases in price, a consumer is more likely to switch to a product of the same type. We should note that a similar difference can be seen when considering the origin of the spirit; both American and foreign brands observe higher cross-price elasiticities with other American (foreign) brands than with the opposite. These were obviously not nested categories.

Table 5.1 displays the elasticities of a sample market graphically. One can observe the darker colors on the diagonal; these correspond with the higher values (in absolute value) of the own-price elasticities. The cross-price elasticities are all extremely close to zero, indicated by the yellow color.

The mean diversion ratios to the outside good are quite high and positive. The diversions ratio to the outside good tells us the fraction of consumers who leave product j after a price increase and then choose the outside option. The high values of the diversion ratio suggest a strong substitution effect between the products considered in our market. This is especially true for the BLP model, more so than RCNL.

Finally, we find an estimated aggregate elasticity of demand of -0.017 and -0.029 with BLP and RCNL respectively. Table 5.2 also plots the distribution of the market-mean own-price and aggregate elasticities. The lower values of the aggregate elasticties are consistent with what is typically seen in market analysis: demand for an entire category is generally less elastic than demand for only a single product.

5.3 Discussion

The estimates of the price elasticities found by the RCNL model at first seem to paint a grave picture for policy makers: demand for spirits can be concluded to be inelastic, meaning that an increase in prices through taxation will have little effect. However, as discussed by Kumar (2017),the small magnitude of the elasticities does not mean that tax policies are ineffective, it merely implies that the effect they have will be modest. If anything, the inelasticity of the demand for spirits provides more evidence that the more drastic measure of full prohibition should not be taken; if people are not very responsive to price changes then prohibition will probably lead to the emergence of black markets and smuggling, as discussed in Chapter 1.

The mean own-price elasiticity of -0.14 estimated by the RCNL model compares reasonably with other findings. Although on the lower end of the range found by Gallet (2007) and Wagenaar et al. (2009), it is not a complete outlier, as both meta analyses include reports of lower elasticities. Also

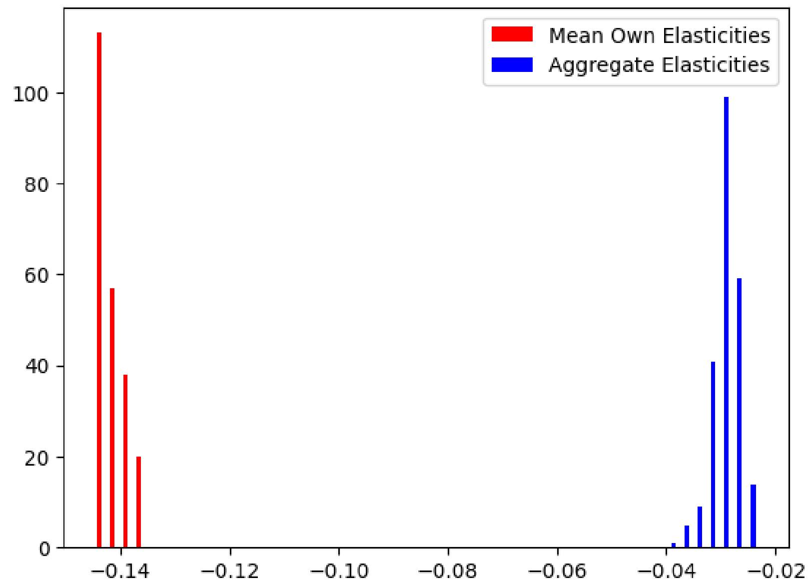


Figure 5.2: Histogram showing the distribution of the mean own and aggregate elasticities

note that Fogarty (2010) found that approximately a quarter of price elasticities were lower than 0.2, further evidence that our estimate is reasonable.

We should also remark that in this thesis we have only analyzed the purchases of spirits for off-the-premises consumption. Sousa (2014), in his literature review, makes the remark that only recently papers have began to distinguish between off- and on-the-premises consumption. In his review, elasticities limited to off-the-premises consumption in papers that that make this distiction were found to vary between -0.08 and -0.9, again pointing towards large variation.

5.4 Limitations and future work

This thesis is not without limitations. Most likely the largest improvement that can be made upon the model formulation, is the inclusion of demographics. In our model formulation, the random coefficient on price follows is composed of a mean part and a part that follows a standard normal distribution. It is an option to include another term: one that follows an empirical non-parametric distribution known from certain data-sources. This demographic part might include variables like age, income, education, gender etc. Including demographics would add additional information and also reduces the reliance on parametric assumptions (Nevo, 2000). Including demographics might be particularly relevant for future research where BLP or RCNL is applied to the analysis of spirits or other alcoholic beverages. Notably, controlling for factors such as income and age might prove to be useful as these most likely have significant implications for one's willingness to buy a certain product for the given price.

A second possible extension of the analysis is the specification of supply-side variables. As Nevo (2000) remarks, the model can easily be extended by adding moment conditions to the GMM-objective function, at little computational cost. The advantage of estimating demand and supply jointly is that it increases the efficiency of the parameters, i.e. it reduces the variance.

A third shortcoming of this analysis is that we do not perform any counterfactual experiments. Counterfactual analysis may include simulating the introduction of a tax, which allows us to analyze how the market dynamics would change under such a measure. This could provide additional useful information for conducting policy analysis. It might either provide more evidence for our findings that demand is very inelastic and therefore not going to be dramatically altered by a tax, or it might lead us to nuance the findings of the elasticities.

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Appendix A

Selected products and their characteristics

Table A.1 shows the top 28 most frequently sold products between Q1-2012 and Q3-2016, with their alcohol percentage, category and origin.

Item	Alcohol Percentage	Category	Origin
Absolut Swedish Vodka 80 Prf	40.0	vodka	Swedish
Admiral Nelson Spiced Rum	35.0	rum	American
Bacardi Superior Rum	44.5	rum	Bermudian
Bailey's Original	17.0	whiskey	Irish
Black Velvet	40.0	whiskey	Canadian
Black Velvet Toasted Caramel	40.0	whiskey	Canadian
Captain Morgan Original Spiced	35.0	rum	American
Crown Royal	40.0	whiskey	Canadian
Fireball Cinnamon Whiskey	33.0	whiskey	Canadian
Five O'clock Vodka	40.0	vodka	American
Hawkeye Vodka	40.0	vodka	American
Hennessy Vs Cognac	40.0	cognac	French
Jack Daniels Old #7 Black Lbl	40.0	whiskey	American
Jagermeister Liqueur	35.0	liquer	German
Jameson	40.0	whiskey	Irish
Jim Beam	40.0	whiskey	American
Jose Cuervo Especial Reposado Tequila	38.0	tequila	Mexican
Kinky Liqueur	40.0	liquer	American
Malibu Coconut Rum	21.0	rum	Barbadian
Mccormick Vodka	40.0	vodka	American
New Amsterdam Vodka	37.5	vodka	American
Patron Tequila Silver	40.0	tequila	Mexican

Item	Alcohol Percentage	Category	Origin
Rumchata	15.0	rum	American
Smirnoff Vodka 80 Prf	37.5	vodka	Russian
Southern Comfort	35.0	whiskey	American
Templeton Rye	40.0	whiskey	American
Titos Vodka	40.0	vodka	American
Uv Blue Vodka	30.0	vodka	American

Table A.1: 28 products that were selected for this analysis with their characteristics

Appendix B

Python Code

The Python code that was used to perform the analysis can be downloaded through this link: https://github.com/bastenhuisman/Bachelor-Thesis-Basten-Huisman

Table B.1 shows the pacakges that were used in this analysis, with the corresponding version:

Package	**Version**
Numpy	1.23.4
Pandas	1.5.1
PyBLP	1.1.0

Table B.1: Packages used in Python code