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Price Elasticity of Alcohol Demand: A Meta-Analysis

Master's thesis

Author: Anita Boško
Study program: Economics and Finance
Supervisor: PhDr. Tomáš Havránek, Ph.D.
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Declaration of Authorship

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Prague, July 31, 2020

Anita Boško

Abstract

The main objective to this meta-analysis is to estimate the price elasticity of alcohol demand after correcting for publication bias and to identify the attributes that explain the data heterogeneity. By employing a funnel asymmetry test, this study confirms and corrects for the presence of the publication bias and suggests that price elasticites for wine and spirits have decreased. This finding is in line to the changing drinking patterns, where wine and spirits become more attractive beverages then beer. A stronger publication bias has been confirmed also under the assumption of nonlinearity, which is derived by applying the "stem-based" method. To account for model uncertainty we use Bayesian model averaging and derive that the length of the data, highly frequency data and estimates under the specification for unconditional demand function, contribute the most to the data heterogeneity. Heavy drinkers are not responsive to the price changes, exhibiting a totally inelastic alcohol demand. Country development is important and low and medium income countries may affect the estimated alcohol price elasticities.

JEL Classification	C11, C81, I18, D12
Keywords	alcohol, demand, meta-analysis, price, elasticity, Bayesian model averaging
Title	Price Elasticity of Alcohol Demand: A Meta-Analysis

Author's e-mail	`anita.colovik@gmail.com`
Supervisor's e-mail	`tomas.havranek@ies-prague.org`

Abstrakt

Hlavním cílem této metaanalýzy je odhadnutí cenové elasticity alkoholu a identifikace atributů, které vysvětlují heterogenitu dat po korekci publikační selektivity. Tato studie potvrzuje a upravuje výskyt publikační selektivity použitím testu trychtýřové asymetrie a naznačuje, že se elasticita ceny u vína a lihovin snížila. Toto zjištění se shoduje s měnícími se zvyklostmi v oblasti konzumace, kdy se víno a lihoviny stávají atraktivnějšími nápoji než pivo. Publikační selektivita je také nejsilnější za předpokladu nelinearity, což bylo potvrzeno aplikací "stem-based" metody. Bayesovské průměrování modelů bylo využito pro objasnění nestability modelu, na tomto základě odvozujeme, že množství dat, jejich

frekvence a odhady specifikované funkcí bezpodmínečné poptávky, nejvíce přispívají k heterogenitě dat. Těžcí pijáci nejsou příliš reaktivní na změnu ceny, a tak vykazují naprosto nepružnou poptávku po alkoholu. Důležitý je také stupeň rozvoje ve zkoumané zemi, protože země s nízkými a středními příjmy mohou ovlivňovat odhadovanou elasticitu ceny alkoholi.

Klasifikace JEL	C11, C81, I18, D12
Klíčová slova	alkohol, poptávka, metaanalýza, cena, elasticita, Bayesovské průměrování modelů
Název práce	Cenová Elasticita Poptávky po Alkoholu: Meta-Analýza
E-mail autora	anita.colovik@gmail.com
E-mail vedoucího práce	tomas.havranek@ies-prague.org

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Acronyms

BMA Bayesian model averaging

DALY Disability-adjusted life years

EU European Union

FAT Funnel-asymmetry test

HIC High income countries

LMIC Low and medium income countries

MCMC Markov chain Monte Carlo method

OLS Ordinary least squares

PET Precision-effect test

PIP Posterior inclusion probability

PMP Posterior model probability

UIP Unit information prior

Master's Thesis Proposal

Author	Anita Boško
Supervisor	PhDr. Tomáš Havránek, Ph.D.
Proposed topic	Price Elasticity of Alcohol Demand: A Meta-Analysis

Motivation Alcohol has been consumed in many different forms and in different occasions. We can freely say it is an important part of our lives, influencing us directly or indirectly, throughout its many negative and some positive externalities. Many alcohol related policies, and how they address important public health issues, depend highly on the alcohol price elasticities. Hence the great importance to study the sensitivity of alcohol demand, since these kind of studies will serve as a reference to the government and health authorities in creating effective policies to discourage the over-consumption of alcohol. However, price elasticity estimates of alcohol demand vary among different studies and are heterogeneous across beverages, countries, level of country development, time, age, gender, level of education etc. A meta-analysis summarizes all these reported estimates and provides a reliable quantitative indicator that will serve as a powerful tool for the policy makers in the process of carving effective public policies.

There have been several meta-analyses on the price elasticity of alcohol (Gallet 2007; Wagenaar *et al.* 2009; Fogarty 2010; Nelson 2013; Fanta 2014). These studies evolved throughout time. They explore the heterogeneity in literature, some of them corrected for precision. And most importantly, in the newer studies (Nelson 2013; Fanta 2014), even the publication bias is considered.

Hypotheses

Hypothesis #1: The level of country development does explain the variation across countries.

Hypothesis #2: There is a negative bias in the reported results, but it decreases over time.

Hypothesis #3: Heavy drinkers exhibit lower magnitude of price sensitivity.

Methodology By the mean of the funnel plots, the presence of publication bias in the literature will be firstly visually examined. Numerical values to the publication bias will be then assigned with the application of the funnel asymmetry regression test, which will consider different test specification. Publication bias will be also examined under the assumption of nonlinearity, by employing the "stem-based" method created by Furukawa (2019). At the end, the presence of heterogeneity and identification of the best fitted model will be exhibited by the Bayesian model averaging.

Expected Contribution I have extended the dataset to the latest available data. The data also contains price elasticity estimates for the low and medium developed countries, which was not the case in the previous meta-analyses, as they are mostly compiled of data from developed countries. Considering the increasing trend of alcohol consumption for these countries and also the fact that they bear the highest disease burden from alcohol consumption per capita, this meta-analysis will give us an oversight of the alcohol price responsiveness in these countries. The presence of the publication bias will be also examined under the condition of nonlinearity, by applying a relatively new technology (Furukawa 2019). Furthermore model uncertainty will be considered and after applying the Bayesian model averaging it will be identified which variables contribute to the heterogeneity the most. This is the first meta-analysis on the topic of price alcohol elasticity to apply the Bayesian model averaging and nonlinear techniques for publication bias assessment.

Outline

1. Introduction: Negative externalities from extensive alcohol consumption cause significant damages the society and peoples' lives. Understanding the demand responsiveness to alcohol price changes is therefore very important, since the measurements against alcohol consumption will highly depend on the elasticity (or inelasticity) of alcohol demand.

2. Trends in alcohol consumption: Alcohol consumption has a decreasing trend, especially in developed countries. However alcohol-attributed harms to society still remain high.

3. Strategies and previous research: Public policy should be constructed in such a way that will affect mostly the heavy drinkers, since they are the one attributing the most to the negative externality of alcohol consumption. Excise taxes on alcohol are proven to be one of the most efficient policies in reducing alcohol consumption. Meta-analysis summarizes the available literature and

provides an important reliable indicator to the policy makers. As the literature extends and new researches are available, there is also a need for new extended meta-analysis, where new techniques will be considered.

4. Dataset: Data from Fogarty (2010) and Fanta (2014) have been used as a base, but we extended the dataset to recent available estimates.

5. Methods: In order to asses the publication bias in the literature, a funnel plots and several specifications for the funnel asymmetry test have been applied. Publication bias will be also confirmed by a "stem-based" method, which is a nonlinear method created by Furukawa (2019). At the end the model uncertainty will be considered by applying the Bayesian model averaging method.

6. Results: It will be discussed to what extent the literature has been influenced by publication bias and also the variables contributing the most to the heterogeneity of the price elasticity will be identified.

7. Conclusion: At the end, the findings from the research will be summarized, and fields for future research will be pointed out.

Core bibliography

Fernandez, C., E. Ley, & M. F. Steel (2001): "Model uncertainty in cross-country growth regressions." Evidence, and a New Correction Method 12(4): pp.334-347.

Fogarty, J. (2010): "The demand for beer, wine and spirits: A survey of the literature." Journal of Economic Surveys 24(3): pp. 428-478.

Furukawa, C. (2019): "Publication bias under aggregation frictions: Theory, evidence, and a new correction method." American Economic Review 109(8): pp. 2766-94.

Havranek, T. & Z. Irsova (2017): "Do borders really slash trade? A meta-analysis."IMF Economic Review 65(2): pp. 365-396.

Nelson, J. (2013): "Meta-analysis of alcohol price and income elasticities - with corrections for publication bias." Health Economics Review 3(1): pp.1-10.

Stanley, T. D. (2005): "Beyond publication bias." Journal of economic surveys 19(3): pp. 309-345.

Chapter 1

Introduction

Alcohol is no ordinary commodity because of its addictive nature, and because when consumed excessively it can cause significant harm to both the individual and the wider society. And despite the decreasing trend of alcohol consumption, alcohol related harms to society remain high. Alcohol consumption is one of the leading risk factors for population health distortions and many social problems worldwide. It is associated with esophageal cancer, epileptic seizures, chronic pancreatitis, liver cirrhosis (Vitaliano 2015; Rehm *et al.* 2006; Schwartz *et al.* 2013), road injuries, (Cobiac *et al.* 2019), domestic violence, homicide (Keyes *et al.* 2019; Naimi *et al.* 2016), loss of productivity (Pryce *et al.* 2019), household poverty (Kumar 2017; Laković *et al.* 2019) and others. In 2016, the harmful use of alcohol resulted in around 3 million deaths worldwide (5.3% of all deaths) and 132.6 million disability-adjusted life years (DALYs)[1] - 5.1% of all DALYs, that same year. From all deaths among those who are 20-39 aged, 13.5% were associated with alcohol. Deadly injuries attributed to alcohol were estimated to be 0.9 million, from which 370 000 deaths were due to road injuries, additional 187 000 deaths of people other than drivers, 150 000 due to self-harm and around 90 000 due to interpersonal violence (WHO 2019).

Beside the negative consequences of alcohol consumption, when consumed in small quantities, it can also have positive effects on health, like increasing the level of good (HDL) cholesterol and reducing the risk of heart and vascular diseases (Estruch *et al.* 2013). Moderate drinking has been also related to beneficial socialization and networking effects, as well as better labour market outcomes (Ramful & Zhao 2008). However, the lack of studies on positive

[1]DALY is measure that can be thought as a lost of healthy years life, due to ill-health, disability or early death.
$https://www.who.int/healthinfo/global_burden_disease/metrics_daly/en/$

externalities, leaves this topic rather controversial. But even with the benefits at hand, the cost for the society from the over-consumption of alcohol are enormous, therefore alcohol consumption has been and still remains one of the major public health priorities.

How efficient the authorities would be in diminishing the negative externalities from the extensive alcohol consumption depends highly on the understanding of the price responsiveness to alcohol demand. The magnitude of consumption reduction is captured by the price elasticity of alcohol demand, which is the change in demand of alcohol as a result of a unit change in its price, keeping all the other factors (i.e. income, price of other products) constant. Price elasticity on alcohol demand follows the "demand law" and exhibits an inverse relationship between the price and demand. That is, in case of inelastic alcohol demand the price elasticity would be $<$ - 1 or the percentage change in demand is less than the percentage change in the price of alcohol. Recent meta-analyses (Gallet 2007; Wagenaar 2010; Fogarty 2010) estimated the price elasticity of alcohol to be around -0.5. This implies that 10% rise in alcohol price will be followed by a decreasing demand for alcohol by about 5%. One of the objectives of this thesis is to examine the true price elasticity effect of alcohol on updated dataset to recent studies. By the mean of meta-analysis techniques, we will derive to a lower price elasticity, or in average -0.3 across all alcohol beverages and show that there is a decreasing trend, especially in the price elasticity estimates for wine and spirits. Under some specification this study suggests that the true effect on alcohol price elasticity might be even as low as -0.15. This would certainly suggest that in case of low or perfectly inelastic alcohol demand, there will be lesser or no effect on the consumption by any alcohol price changes. Taxation policies are clearly tied to the price elasticity (or inelasticity) of alcohol demand, therefore it is important to understand the price elasticity of alcohol in line with the consumer preferences as well, since price elasticity might vary substantially across studies, different beverages, countries, time and whether the elasticity estimate is elastic, unit elastic or inelastic. We will also identify the set of variables that contribute to the changing patterns of the alcohol price elasticity, by accounting for 23 different aspects of the studies.

The reminder of this thesis is organized as follows. Chapter 2 gives an oversight of the alcohol consumption and the changing patterns in the recent years. Chapter 3 is dedicated to the public policy strategies against the alcohol consumption as well as the recent meta-analyses. Chapter 4 closely examines

the updated dataset. We continue in Chapter 5 to investigate the presence of publication bias by applying the asymmetry funnel test and the "stem-based" technique that performs under the assumption of nonlinearity. Chapter 6 examines the data heterogeneity by the Bayesian model averaging and the last Chapter 7 concludes the thesis.[2]

[2]Data and code to this thesis is available upon request

Chapter 2

Trends in alcohol consumption

There have been many studies on alcohol, where authors try to examine the effect that alcohol has on different aspects of society. It can be said it is a complex topic, since the effects depend on many attributes, and it affects many important aspects of society and also personal lives. No one can be isolated from the direct or indirect effects from alcohol consumption. Therefore, and regardless of many studies on alcohol, this topic never becomes entirely exploited and new evidence is always welcome to support the future policies.

In a report authorized by the European Commission, conducted by RAND Europe[1] (Rabinovich *et al.* 2009), it has been shown that alcohol became more affordable in most of the EU countries since mid - 1990s -, in terms of changes in the real disposable income and the relative price of alcohol. Notably, alcohol became more affordable for the younger group of the population, that is those between 16-24 years old. They also found a positive correlation between increased affordability and alcohol consumption, where 1% increase in alcohol consumption was linked to an increase of 0.85% in fatal traffic accidents, 0.61% in traffic injuries, and 0.37% of the incidence of liver cirrhosis within the same year. However no significant relationship was found to homicides.

Interestingly, although alcohol affordability increases, there is a decreasing trend in alcohol consumption on aggregate level, with countries from the European regions exhibiting the highest decline in alcohol consumption per capita. On the other hand, especially developing countries from Western Pacific Regions and South-East Asia report increasing alcohol consumption. However on

[1]RAND Europe is an independent, not-for-profit research organisation that aims to serve the public interest by improving policymaking and informing public debate. Its clients are European governments, institutions and firms with a need for rigorous, impartial, multidisciplinary analysis.
https://www.rand.org/randeurope.html

a global level, and in absolute values, the decreasing alcohol consumption trend is still higher than the increases. And yet the European countries, with 9,8l in 2016 alcohol consumption per capita, are the regions with the highest level of alcohol consumption in the world (Rabinovich *et al.* 2009; WHO 2019).

The above said could be clearly seen, if we compare alcohol consumption data per capita, from year 1996 to 2016 [2] (Table 2.1). The comparison is made for the three main alcohol beverages, beer, wine and spirits and in liters of pure alcohol. As we can see the highest dropdown in alcohol consumption could be seen in beer consumption, and with the high income countries exhibiting the highest fall, i.e. almost 50% for Denmark, Ireland and New Zealand. All three have increased consumption of wine, even spirits in case of New Zealand. Spain and Italy register the highest fall in wine consumption, but increase in beer consumption. However decreased consumption in one beverage is not entirely compensated by another beverage, thus the decreasing trend of total alcohol consumption. But these shifting patterns from one to another beverage signify changing of drinking preferences. Namely "beer drinking" countries, become more "wine-drinking" or in the case of Italy and Spain the other way around. The same could be said for Russia as a "spirit-drinking" country, now switching more to beer consumption. The highest beer consumption increase could be assigned to Poland, but more importantly to the low income countries, like India, Thailand and Vietnam. Increased wine consumption could be witnessed in Ireland and Norway, whereas increasing spirits consumption in Vietnam, India and New Zealand. Although the amount for India is pretty small (0.24l per capita), it is significant to notice that in 1996, this country had almost no registered spirit consumption (only 0.02l per capita). Total alcohol consumption should be considered only informative, since we do not include the worlds total alcohol consumption, but the pattern is obvious when we compare the individual countries as well - people tend to drink less beer and switch rather to drinking more wine or spirits.

Declining trend of alcohol consumption and shifting preferences can be ex-

[2] Data are extracted from the World Health Organization Global Information System on Alcohol and Health, accessed from *https://apps.who.int/gho/data/node.main.A1022?lang=en*. We decide to compare the latest available data, that is 2016 to 1996, since we further in our research use database from Fogarty (2010), where he analysis the alcohol consumption in 1996. We also find that range of 20 years is long enough to exhibit any changing patterns in alcohol consumption. We include more countries for comparison, and these are the countries we extended Fogarty's dataset to the recent years. For (Country)* no data was available for year 2016, instead we took data from 2015.

plained by change of taste and habits, which normally could come from real income changes. For example, one can afford to drink wine instead of beer - as we can see this pattern mostly with the high income countries. Or simply people dedicate themselves to healthier life styles and decide to drink less.

Table 2.1: Alcohol consumption per capita(+15) in 1996 and 2016

1996			Country	2016		
Beer	**Wine**	**Spirits**		**Beer**	**Wine**	**Spirits**
5.32	2.74	1.7	**Australia**	3.87	3.64	1.25
4.33	1.14	1.9	**Canada**	3.7	2.1	2.1
2.39	2.45	2.59	**Chille***	2.85	2.61	2.43
0.95	0.2	3.33	**China**	1.7	0.18	3.86
7.69	2.18	3.91	**Czechia**	6.92	2.77	3.3
3.3	2.14	3.04	**Cyprus***	2.84	2.71	4
7.14	3.78	1.35	**Denmark**	3.57	4.27	1.63
4.43	1.48	1.08	**Finland**	4.11	1.74	1.81
2.45	8.18	2.87	**France**	2.21	6.9	2.43
7.29	3.06	2.77	**Germany**	5.74	3.1	2.07
0.03	0	1.89	**India**	0.23	0	2.81
9.53	1.08	2.36	**Ireland**	5.39	3.21	2.15
1.41	6.98	0.7	**Italy**	1.8	4.58	0.69
3.24	0.21	2.87	**Japan***	1.25	0.38	2.74
0.81	0.01	0.7	**Kenya***	0.74	0.03	0.4
5.05	2.6	2.15	**Netherlands***	3.83	2.88	1.32
6.1	2.31	1.53	**New Zealand**	3.46	3.08	2.67
2.88	1.12	1.02	**Norway**	2.65	2.21	1.01
2.52	0.97	4.52	**Poland**	5.85	0.82	3.76
3.87	7.53	0.7	**Portugal**	2.79	6.55	0.82
1.51	0.79	6.91	**Russia**	3.29	1.08	3.25
3.93	3.97	2.86	**Spain**	4.64	1.55	2.39
3.65	1.81	1.44	**Sweden**	2.61	3.43	1.01
3.53	5.85	1.83	**Switzerland**	3.03	4.54	1.75
0.81	0.03	5.26	**Thailand**	1.86	0.18	4.53
5.29	2.09	1.75	**UK**	3.44	3.5	2.21
4.66	1.14	2.38	**USA***	4.13	1.59	3.07
0.6	0	0.02	**Vietnam**	2.83	0.02	0.24
104.71	**65.84**	**65.43**	**Total**	**91.33**	**69.65**	**61.70**
3.74	**2.35**	**2.34**	**Mean**	**3.26**	**2.49**	**2.20**

[a] *Source:* World Health Organization Global Information System on Alcohol and Health
[b] *Note:* Alcohol is recorded in liters of pure alcohol

The downward trend of alcohol consumption however suggests, that if the affordability of the alcohol beverages, had remained constant, then we would have seen a greater decrease in the overall alcohol consumption. At the first sight it seems contradictory, that overall alcohol consumption is decreasing,

and at the same time there is a positive relationship between affordability and alcohol consumption, but let us not forget that alcohol consumption, and alcohol related harms, could be influenced by a number of factors, such as, increasing competition from other types of beverages, like for example ready-to-drink beverages, or the non-alcoholic drinks, then the nature and the strictness of the public policies, national development, local culture, or urbanization, the level of education, socio-economic background, age, gender and many more.

Therefore it is important to understand the responsiveness of drinking, with respect to price changes, since based on the quality of this information, it will depend how effectively will the public policy fight the negative externalities attributed to alcohol consumption.

Some studies show that there is an inverse relationship between the volume of consumption and elasticity (Selvanathan & Selvanathan 2007; Fogarty 2010). In terms of the consumption pattern as we show in the Table 2.1 it would suggest some changing pattern in the price elasticities as well. Earlier meta-analyses exhibit price elasticities where the beer has the lowest price elasticity and wine and spirits being more price elastic. Fogarty (2010) for example derived weighted random estimates to -0.36, -0.57 and -0.52, for beer, wine and spirits respectively. Other authors displayed the same pattern where beer is the least elastic beverage (Nelson 2013; Wagenaar *et al.* 2009). Later on in this paper when we estimate the price elasticity of alcohol demand (Chapter 5), we arrive to a different pattern, where under some specifications, beer is not always the least elastic beverage, although being close to what the literature suggest. Estimates from the new updated dataset are however closer to each other, with a difference in magnitude of 0.1. For example we derive following true effect OLS estimates, -0.304, -0.322 and -0.418 for beer, wine and spirits, where it is obvious that wine and spirits estimates have decreased, hence closer to the price elasticity of beer. New estimates are in line with the consumption pattern presented in Table 2.1, where for example the high income countries (HIC) drink less beer, and switch more to wine and spirits. Increasing drinking pattern in all beverages was also clear in low and medium income countries (LMIC), hence the assumption of inverse relationship of alcohol consumption to elasticity, explains as well the decreased price estimates for wine and spirits. In Chapter 6 when we will explore the heterogeneity across the countries in more details, our findings will indicate that the developed countries are more responsive to alcohol price changes compared to the developing countries and that the developing countries are the one that contribute to the data varia-

tion the most. This is an important aspect for the policy makers, suggesting that they should concentrate more on the increasing drinking patterns in the developing countries, considering also a less responsive alcohol price demand. They should for sure account for a less restrictive taxation policy and investing more into non-price based policies. Next chapter summarizes both price-based and alternative alcohol policies as a measurements against over-consumption of alcohol.

Chapter 3

Strategies and previous research

3.1 Public policy targets

Highly of interest to the policymakers is reducing the average population-level alcohol consumption. Herewith, the price elasticity of alcohol is one of the main indicators that will determine alcohol related strategies. The efficiency of the relevant public policy, will depend on how responsive are those who contribute the most to the total alcohol consumption and additionally misuse alcohol. On the other hand, those who enjoy alcohol without causing any external cost should be less affected. Since price responsiveness is heterogeneous among different subgroups and alcohol beverages, it is highly important to understand how alcohol price changes will affect the demand among different subpopulation groups.

Average consumption is determinated mostly by the prevalence of heavy drinking, and they bear the highest cost for the society. For example in some countries, like Russia, where there is an extended history of heavy and hazardous alcohol drinking, even being labeled as "drinking culture" the consequences of alcohol consumption are equal to catastrophic. Leon *et al.* (2007) estimated that only for region of Izhevsk [1], 43% of men deaths aged 25-54, can be associated with heavy and frequent drinking. In the UK, 79% alcohol is consumed by 30% heaviest drinkers in the UK (Meier *et al.* 2010). Additionally one other concerning issue is the evidence of an increasing trend for excessive forms of alcohol drinking like binge drinking, especially among young people (Naimi *et al.* 2016; Xuan *et al.* 2015; Goryakin *et al.* 2015).

[1] Region in central Russia, with around 650.000 inhabitants
https://en.wikipedia.org/wiki/Izhevsk

Therefore, the policymakers will mostly try to affect the heavy drinkers. However there is extensive empirical evidence that shows that heavy-drinkers have inelastic alcohol demand, so higher taxes or prices will have no effect in reducing their alcohol consumption and negative externalities. Conversely, we will find moderate to low drinkers affected more by it (Ayyagari *et al.* 2013; Nelson 2014; Ruhm *et al.* 2012; Meier *et al.* 2010). Wagenaar *et al.* (2009), estimates the price elasticity for alcohol demand for heavy drinkers to be -0.28. It is also likely that when prices of alcohol increase, this group will not change the quantity of alcohol consumption, but they will just switch to cheaper alcoholic products (Pryce *et al.* 2019). This theory is also challenged by some authors, suggesting the opposite, that heavy drinkers are highly responsive to prices (Keyes *et al.* 2019; Xu & Chaloupka 2011; Dave & Saffer 2008). It is obvious that the policymakers have no easy job to do, and should always consider that the price elasticity substantially varies across beverages, drinking patterns, countries, econometric methods and demand function specification.

Another trend that draws the attention for further investigation is the increase of alcohol consumption in developing countries. Increasing wealth in these countries, thus alcohol affordability, goes hand in hand with the increased alcohol consumption (Laković *et al.* 2019; Chelwa *et al.* 2019). We have noticed this trend also when we discussed the consumption pattern in the previous chapter (Table 2.1). More important is that the poorer and low income countries, exhibit higher disease burden per liter of alcohol than high income countries (Anderson *et al.* 2009; WHO 2019). In India, as reported by the Ministry of Home Affairs, of the Government of India, and cited by Kumar (2017), for example, 15 people die every day or 1 every 96 minutes from the harmful effects of alcohol consumption. Although there is a vast literature on alcohol consumption, mostly they are focused on the developed nations, and there is a lack of research of the effects, for the developing countries. It is something that should be taken into consideration for future researches.

3.2 Strategies to reduce alcohol consumption

An effective alcohol control measure is in the interest of public health, therefore the governments undertake different strategies, which depend on the previous researches, but also are subject of continuous changes and improvement.

Price-based intervention, such as increasing alcohol taxation, introducing a minimum unit price, or banning alcohol promotion, have proven to be an effec-

tive way to reduce alcohol consumption and related health and social problems in society (Anderson *et al.* 2009; WHO 2019; Chaloupka *et al.* 2002). Price elasticity of alcohol demand sets the basis on which the relevant alcohol policies are build.

Effective alcohol policies protect the health of population. Almost 95% of countries have alcohol excise taxes, but almost half of them use also a combination of other price strategies, such as adjusting taxes to keep up with inflation and income levels, imposing minimum pricing policies, or banning below-cost selling or volume discounts. However, non-price based interventions like regulations on physical availability of alcohol (via reduced hours of sale) and restriction on alcohol advertising have been applied less (WHO 2019).

Alcohol policies and how they will be set depends on the price elasticity of alcohol. Additional tax burden, should not reduce light to moderate drinkers consumption level, rather it should target heavy drinkers, since then the intervention could attribute to reducing health costs and decreasing social problems (Aepli 2014).

3.2.1 Minimum price policy

Minimum price policy means setting a floor price per unit of alcohol, below which it is illegal to sell alcohol. Increases in minimum price can substantially reduce alcohol consumption. For example, in Canada, findings show that a 10% increase of the minimum price resulted in reduced consumption by 6.8% for spirits, 8.9% for wine and by 1.5% for beer (Stockwell *et al.* 2012).[2]

The importance of this strategy is that it affects mostly cheaper beverages. Since inexpensive alcohol is mostly consumed by hazardous and heavy drinkers it can be easily said, that minimum price policy targets heavy drinkers in terms of harm reduction and consumer spending (Meier *et al.* 2010; Meng *et al.* 2014; Jiang *et al.* 2020; Yeh *et al.* 2013). Introducing a minimum price per unit of alcohol will discourage binge drinking as well, since this instrument will largely affect off-license trade, where alcohol has been mostly purchased (Tomlinson & Branston 2014; Xuan *et al.* 2015). However, it has been criticized that it does not generate fiscal revenues (Araya & Paraje 2018).

Although efficient, this instrument does not have extended usage, as does price taxation. Scotland is the first European country to introduce minimum

[2]Numbers do not relate to alcohol price elasticity. It is only to be considered informative to the minimum price policies and the effect it has to reducing alcohol consumption.

unit price, as of 1 of May, 2018. And although there are some signs for downgrading of alcohol consumption, it is yet too soon to evaluate the effects of it (Scottish-Government 2018).

3.2.2 Taxation of alcohol

On the other hand, there is an extended empirical support for alcohol taxation. It is the most effective strategy for controlling alcohol consumption and reducing alcohol-related harm (Xuan *et al.* 2015; Meng *et al.* 2014; Sharma *et al.* 2017; Byrnes *et al.* 2016).

There are two reasonings behind increasing the taxes on alcohol. One of them is to reduce alcohol consumption through increased alcohol prices (Chaloupka *et al.* 2002), and the second one is increased government revenues (Jiang *et al.* 2020). How efficient tax policy will be in reducing alcohol consumption, reduce externalities, improve public health, or simply raise revenues, will depend on the price elasticity of demand for alcohol. Keyes *et al.* (2019) show that a small tax increase on alcohol reduced heavy drinking and alcohol-related homicide in the urban environment, like New York. For example introducing a 10% tax on alcohol beverages, resulted in a benefit of 1200 lives/per year. Janda *et al.* (2019) as well tried to estimate the optimal level of alcohol taxation in Czech Republic, which in reference to price elasticity will reduce the negative externalities of alcohol over-consumption.

But, whenever the excise taxes are used to reduce the average consumption and alcohol related harms, the cross-border effect should be also considered. This effect could be very influential, especially in the joint markets, such as the European single alcohol market. Since introducing it in 2003, the free trade between the countries was increasing, but so was the competition, which additionally lead to reducing taxes. Namely, people do take an advantage of the lower prices in the neighboring countries. Asplund *et al.* (2007) explore how the demand in Sweden, especially for those closer to the border, is affected by alcohol prices in Denmark or Germany, since both have lower beer and spirits prices, and wine price is about the same. As expected, as the distance increases the response is lesser, but this is an important consideration that should not be ignored, since it could significantly affect the policy measurement each country is considering. For instance, Asplund estimates that a cut in the spirits tax in Denmark in October, 2003, had resulted in 2.2% reduction in the Swedish tax revenues (approximately 15 million Euro per year). Therefore increasing

the taxes in Sweden, hence the prices of spirits will only shift the sales to Denmark or Germany and will not reduce alcohol consumption in total. Rabinovich *et al.* (2009), in the Report for EC address as well the issue with the cross-border purchasing of alcohol. They consider three groups of countries, Sweden-Germany-Denmark, Finland-Estonia and UK-France, where the effects of the cross-border purchasing of alcohol were assessed. Estimated loss in tax revenues, due to cross-border purchase, in the UK were approximated to £150 million. They also find a strong evidence that the increased cross-border purchasing led not only to decreasing tax revenues for the country with higher taxes/prices, but it also increased the consumption of alcohol - a phenomenon witnessed in Sweden and to a lesser extent in Finland, after 2004. Namely when Estonia joined the EU and became a part of the single market for alcohol, Finland reduced the alcohol taxes in order to avoid excessive imports and thereby losses in alcohol tax revenues. As a result, alcohol consumption increased by 10%, from 9.4l in 2003 to 10.3l in 2004, but more importantly alcohol-related harms rose significantly. For example, deaths related to alcohol increased by 31% from 2001-03 to 2004-2006 (Mäkelä & Österberg 2009).

Therefore as we can see, effective alcohol policies can be eroded by international trade, trade agreements, and cross-border issues. And this is something that simply cannot be ignored.

3.2.3 Other limitations

Price related public policy instruments can be effective in reducing alcohol consumption and the negative externalites of it, but there are also some other instruments, which especially in combination with the price related policies can contribute substantially to reducing the harms to the society from overconsumption of alcohol. An effective alcohol strategy is a policy mix of interventions (Rabinovich *et al.* 2009).

Some of those policies include limiting the use of alcohol in particular locations (i.e. drinking in parks or streets, hospitals, or at work), licensing sales, shortening opening times for liquor and other alcohol stores. For example, the homicide rate in Brazil decreased by 44% after prohibiting on-premises alcohol sales after 23.00h (Duailibi *et al.* 2007). Setting minimum age for purchase of alcohol show clear reduction in drunk-driving casualties and other alcohol-related harms (Spach 2017; Rabinovich *et al.* 2009).

Educational anti-drinking campaigns, which will inform about addictive,

intoxicating or adverse health effects of excessive alcohol use, should be addressed to young adults and people from especially low social capital areas, or those groups in the society that exhibit riskier drinking patterns (Rehm *et al.* 2006; Anderson *et al.* 2009; Kumar 2017).

However alcohol industries remain one of the strongest on the global level, therefore many governments face a challenging position to impose some of the decreasing alcohol consumption instruments. Another risk to alcohol consumption is the existence of black unregulated markets. Whenever taxes increase, the effect on alcohol consumption could be eroded by illegal production. Illegal traded alcohol can be even of higher risk to health, and not only because it is cheaper than legal alcohol, thus leading to higher consumption, but because of the unregulated substances contained in this alcohol that can be even more lethal (Anderson *et al.* 2009).

The importance of this topic is immense and the vast literature is a proof of it. The best way to give an oversight to the extensive researches is to conduct a meta-analysis. Although there are some meta-analyses covering this topic, we decided to give an extended research to an updated dataset and by employing new methods and Bayesian Model Averaging method to check for the model uncertainty. Before we continue, we give an oversight to the previous meta-analyses.

3.3 Previous meta-analyses and present study

Considering the importance of this topic and the vast literature written, it is only natural to assume that there have been several meta-analyses on a price elasticity of alcohol conducted.

First that compiled meta-analysis assessing both price and income elasticity on different alcohol beverages (beer, wine, and spirits) was done by Fogarty (2006), followed shortly after by Gallet (2007). They report that the effects results are heterogeneous across studies, depending on the study characteristics (i.e. data used, model specification, estimated method), but interestingly Fogarty (2006) shows that country-specific and beverage specific effects are not important. However, both fail to correct for precision of the estimates, weighting each of the estimates equally and do not correct for heteroscedasticity. To address the dependency across studies, in the cases where the authors had multiple studies, based on the same or similar data, Gallet (2007) used

author-specific dummy variable. But it is not clear how this study handles outliers.

Later on, Fogarty (2010) improves his assessment and departs from the previous meta-analyses, since he accounts for the precision of each estimate. By weighting the estimates by the inverse of the standard error, more weight is to be assigned to an estimate with lower variance. Precise estimates are used for the restricted model, and by applying both full and restricted sample, he corrects for heteroskedasticity. Heterogeneity is addressed by several dummy variables, with special attention paid to theoretical concepts being analyzed (e.g., Hicksian vs. Marshallian price elasticities). Both fixed- and random-effects models are estimated, with the fixed effects mean of -0.26, -0.83 and -0.67 and random effects means of -0.36, -0.57 and -0.52 for beer, wine and spirits respectively, resulting in both models beer to be less elastic in the group of beverages. He handles the outliers by deleting them selectively, and deals with within-study dependency by limiting the estimates to one per study, either by taking the arithmetical average in case of more estimates, or if the author had expressed a clear preference to a model specification, then that was the estimate that was reported. This is the first study to include time trend in its meta-analysis, where the alcohol demand reached its peak around 1953 and started decreasing afterwards.

Wagenaar *et al.* (2009) extended the metadata to 1003 separate estimates of price and tax elasticitites of demand for alcohol from 112 studies. The unweighted means of the reported elasticities are -0.46, -0.69 and -0.80 for beer, wine and spirits respectively. When applying the inverse variance methods for estimates precision, the elasticities decrease to -0.17 for beer, -0.30 for wine and -0.29 for spirits. They also measured the estimates for heavy consumption and resulted with -0.28, across all three beverages. Distinguishing heavy drinkers elasticity from the light ones is important, since heavy drinkers are the ones that contribute the most to society health costs related to alcohol.

By excluding some of the estimates, Wagenaar *et al.* (2009) adjusted for outliers. They compute meta-analysis where the partial correlation coefficients between the alcohol price/tax and alcohol sales or consumption is computed. Although this method is good for comparison of study with different theoretical concepts, it does not really asses the amplitude of price elasticity by beverage. Dependence is addressed by restricting the observation to one per study, but it is not clear how this exclusion was done. Even though beginning with 1003 estimates, in the end only one third of the estimates are analyzed.

Although previous studies addressed heterogeneity and dependence, none of them really handled the issue of the publication bias. Fogarty (2010), concluded it as important, but only for the beer price elasticities and did not correct for it. Nelson (2013) is the first one that demonstrated greater concern for the publication bias. By using funnel graphs and Egger's intercept model, he identified and corrected for the publication bias and alternatively applied the cumulative meta-analysis, initially proposed by Borenstein *et al.* (2009). He deals with the outliers, by employing trimmed samples, along two dimensions: effect-sizes and size of primary standard errors. The within-study dependence is addressed in the same way as Fogarty (2010), leaving one estimate per study. Reported estimates for the Egger-intercept test are -0.172, -0.228 and -0.388, for beer, wine and spirits, which are generally smaller (less elastic) compared to the results in prior analyses and consensus averages.

Fanta (2014) extends the model and the dataset of Fogarty (2010), where he addresses heterogeneity and within-study dependence similarly as Fogarty (2010), and weights the studies with the inverse of the standard error. But he goes one step further by identifying and addressing the issue of the publication bias. By using modern meta-analysis methods, like Eager's intercept test (PET) and Funnel-asymmetry test (FAT), estimated by the mixed-effects method, he derives to significantly different results from the previous meta-analyses. Although estimated elasticities -0.16 for beer, -0.02 for wine and -0.035 for spirits are close to zero, indicating that all three beverages are not price elastic, only the beer price elasticities were significant.

Even though all these meta-analyses found different price elasticities across the three alcohol beverages (beer, wine and spirits), mutual is that beer always exhibits the lowest price elasticity. Price elasticity is negative, following the law of demand and apparently decreasing over time, as Fogarty (2010) and then later Nelson (2013) and Fanta (2014) show.

Interestingly, all previous meta-analyses were compiled for price elasticity originating from developed countries. Therefore it is worth mentioning one recent meta-analysis (Sornpaisarn *et al.* 2013), that considers middle and low income countries alcohol price responsiveness. Meta-analysis is based only on 12 studies, and although they consider only beer as separate beverage, and the other types of alcohols are estimated together, it is an important study that gives us some insight to these groups of countries. Estimates of the random effects model were reported, and even though they adjusted for publication bias, the estimated elasticities were not significantly affected. True effect of the total

alcohol was reported to be -0.64 and for beer price elasticity it was estimated to be -0.50, which is higher than in high income countries, but this might be expected, considering the income constrains in these countries. However, one should not just make plain conclusion before any further analysis, since the result depend on many other characteristics like the applied methodologies, as well as cultural differences. Although literature on price elasticity of demand of alcohol is large, it is obvious that it can be extended with the research from LMICs countries, since the effects of alcohol price and taxation might differ compared to high income countries (HIC).

We conduct our meta-analysis on the dataset from Fogarty (2010) and Fanta (2014), but we extend the database to the latest available data. Importantly, we managed to compile estimates for the low and medium income countries as well, which was not the case in the previous meta-analyses, as they were mostly examining the price elasticity effects in the developed countries. We do not delete any of the estimates collected, as they provide us with more variation to examine the source of heterogeneity in the results and we selectively delete outliers. Publication bias will be addressed and estimates will be corrected for it by the mean of funnel graphs and funnel asymmetry regression test under different specification. We additionally consider the issue of the publication bias under the assumption of nonlinearity, by applying a "stem-based" method, which is a relatively new technique, created by Furukawa (2019). To control for different aspects of the study and to understand the heterogeneity of the data we collect 23 additional variables and we use Bayesian model averaging to account for model uncertainty. As to our knowledge, this is the first meta-analysis on the price elasticity of alcohol to apply a nonlinear technique to consider the issue of publication bias and Bayesian model averaging to deal with the model uncertainty.

Chapter 4

Dataset

In our analysis we use the data from Fogarty (2010), containing data published up to 2007 and the extended dataset from Fanta (2014) up to 2014. By using the same search criteria in SCOPUS as Fanta (2014) did - "alcohol AND price AND elasticity", we check if there are any new published studies up to date. Complementary searches were also conducted using separately "beer", "wine" or "spirits". Our search resulted with 72 studies. In order to not miss any studies, we cross-checked our search in Google Scholar. By reading the abstract, we eliminated firstly those studies that do not report any price elasticity of alcohol demand or instead report cross price elasticity to cigarettes, or drugs. To keep the consistency with the previous dataset, we consider only studies that contain at least one own-price elasticity estimate for one beverage category (beer, wine or spirits) and its standard error. Studies that do not report the standard errors were excluded. We will apply the standard errors for estimate precision and also when we will deal with the publication bias later in this paper. Weighting the estimates to the inverse of their standard errors, assigns more weight to the more precise estimates. Therefore if the study has more than one estimate but reported standard errors, we decided to report all the estimates in that study. Our decision would be also justified when we would test for heterogeneity, and we would want to keep more information that might explain it. Therefore, except from the estimates and their standard error, we also collect 23 variables that represent different characteristics of the data. We would closely examine these variables in Chapter 6. We also do not consider the estimates if they are defined for subcategories of alcohol beverages, unless they could be assigned to the main beverage. For example Srivastava *et al.* (2015), reports estimates for different subcategories (i.e. premium beer, low alcohol beer, red or white wine,

dark and light spirits etc.), but he also provided a within-group share of each of the sub-beverages, which enabled us to calculate the weighted means and standard errors respectively, therefore being representative only for beer, wine or spirits. As a criteria for quality, we consider only published studies. At the end only 10 new studies matched our criteria.

Table 4.1: New studies

Tomlinson & Branston (2014)	Aepli (2014)	Srivastava *et al.* (2015)
French (2016)	Kumar (2017)	Spach (2017)
Stevens & Childs (2017)	Araya & Paraje (2018)	Chelwa *et al.* (2019)
Laković *et al.* (2019)		

The updated dataset consist of 78 studies, and 397 estimates in total. The distribution of different type of beverage is just about the same, with beer and spirits containing 138 and 136 observations respectively, and a bit less for wine, 123 observations. As we can see in Table 4.2, the arithmetic means are almost the same, but medians differ. When we compare it to Fogarty's reported means, -0.44, -0.65 and -0.73, for beer, wine and spirits we can conclude that the price elasticity of beer has increased, whereas wine and spirits' have decreased.

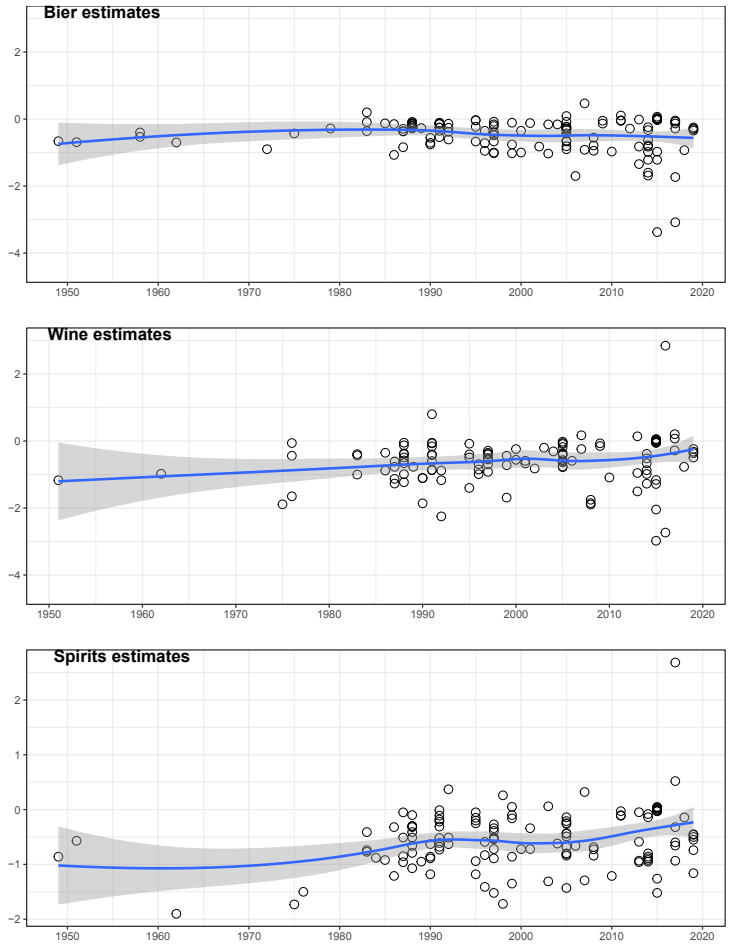
Table 4.2: Summary statistics

	Observations	Mean	Median	SE	Minimum	Maximum
Beer	138	-0.53	-0.29	0.20	-5.07	0.47
Wine	123	-0.56	-0.49	0.25	-2.73	2.85
Spirits	136	-0.52	-0.52	0.20	-1.90	2.68
Alcohol	397	-0.54	-0.41	0.21	-5.07	2.85

This first observation is in line with the drinking consumption pattern, mentioned earlier (Table 2.1), especially for beer. Decreased beer consumption could explain the increased price elasticity. However, we are not to make any firm conclusion yet, since the changes could be a result of some outliers, or authors have started to report more positive estimates in the recent years - which would be the case with the wine and spirits. Both wine and spirits have a maximum values high on the positive scale, whereas the dispersion between minimum and maximum remains high for all three beverages, but for beer is very high on the negative scale. The estimates are very close to each other, which suggests no structural differences across the beverages. We would explore this assumption more in depth in Chapter 6, where we will deal with the heterogeneity of the data.

The oldest published article in our data originates from 1949 and the newest one from 2019. Data range goes from more than one century, beginning from 1870 to 2014. However the topic becomes more attractive after 80's years from the last century, where more articles are being published. We can conclude the same if we look at the Figure 4.1.

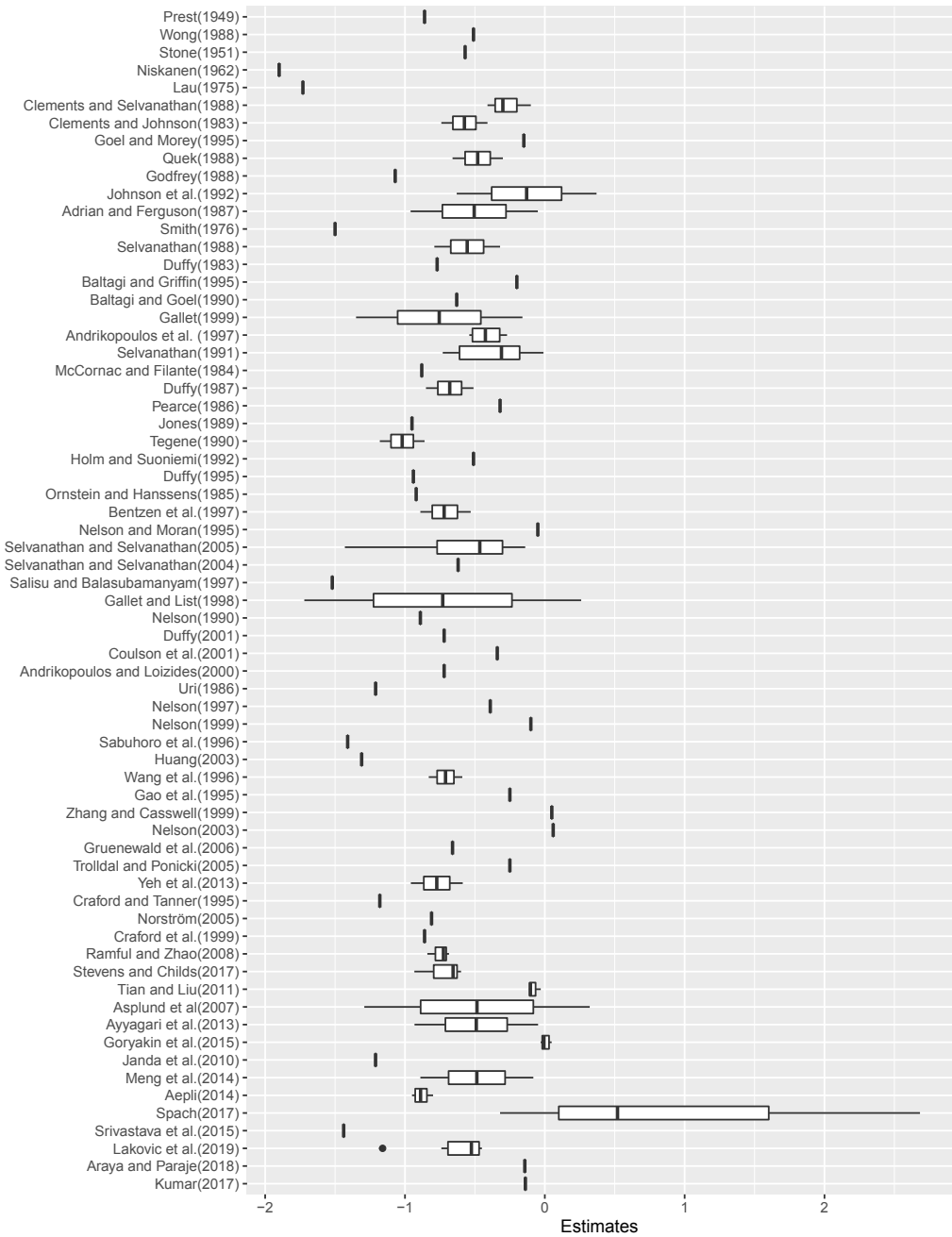
Figure 4.1: Publications over time



On the x-axis are presented publication years, and on the y-axes the reported estimates. The median study in our sample was published in 2003, 2001 and 2000, for beer, wine and spirits, respectively, which indicates that the topic has not lost in importance and more studies are being published. Interestingly, the estimates reported are diverging, where the spirits estimates show the highest dispersion throughout the time, and beer elasticities on the other hand, exhibit a wider distribution in recent history. This variation might be explained with the heterogeneity of the data. Both wine and spirits, have one outlier high on the positive scale, which corresponds to the maximum values

presented in the Table 4.2. Therefore we can reject the assumption that more positive estimates have been reported in recent times. These outliers will be removed later on, when we will inspect for publication bias.

Figure 4.2: Spirits elasticity estimates

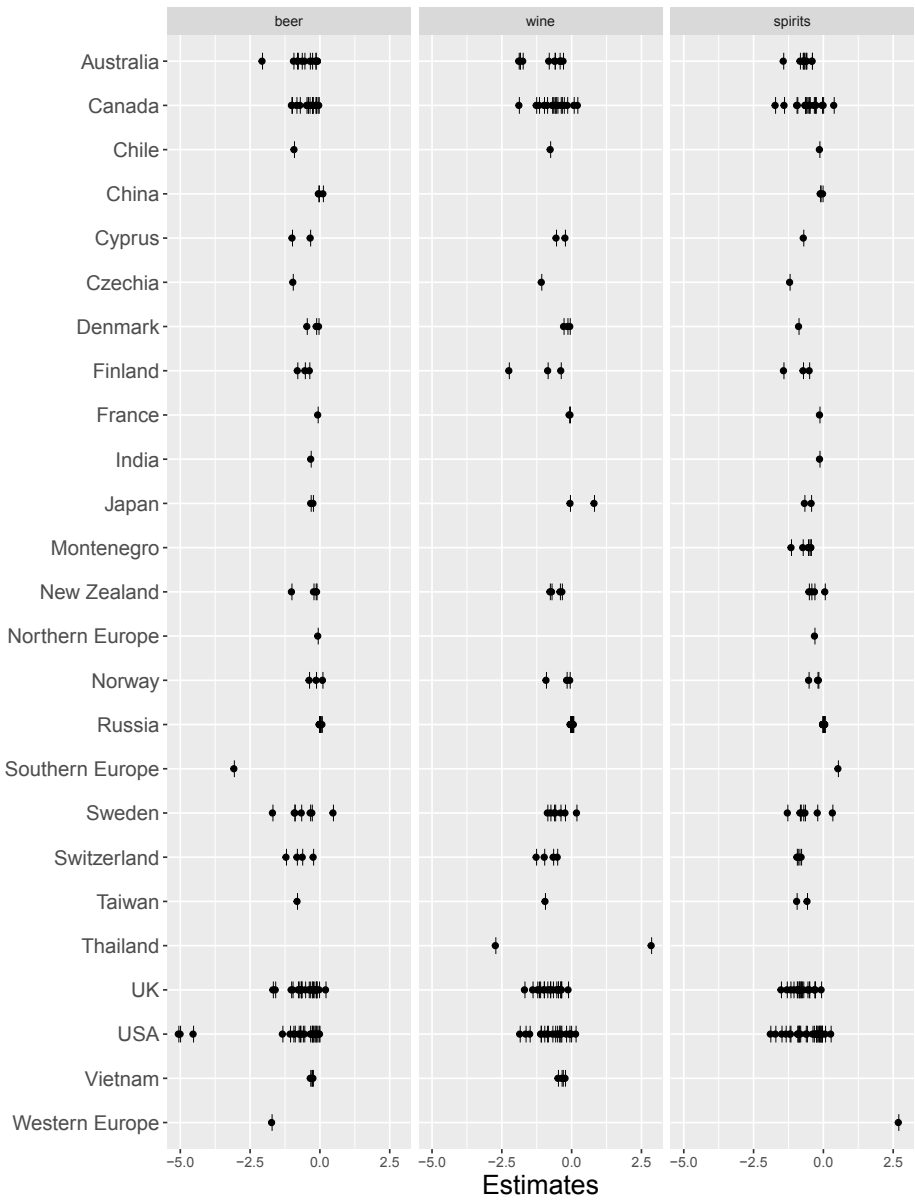


Notes: The figure shows a box plot for the price elasticity for the spirits beverages. Studies are sorted by the mid-year of the sample in ascending order.

Heterogeneity of the data could be also visually examined through out the box plot in Figure 4.2. On the y-axis we have all the studies from this dataset,

ordered in the descending order by mid-year of the data points and on the x-axis, we have the estimates. As we can see the estimates are heterogeneous mostly across the study, not as much within the study. That is, because for most of the studies only one estimate per beverage was reported. Again spirits elasticities exhibit the highest heterogeneity in both within and between studies. Box plots for total alcohol, beer and wine, could be found in Appendix A.

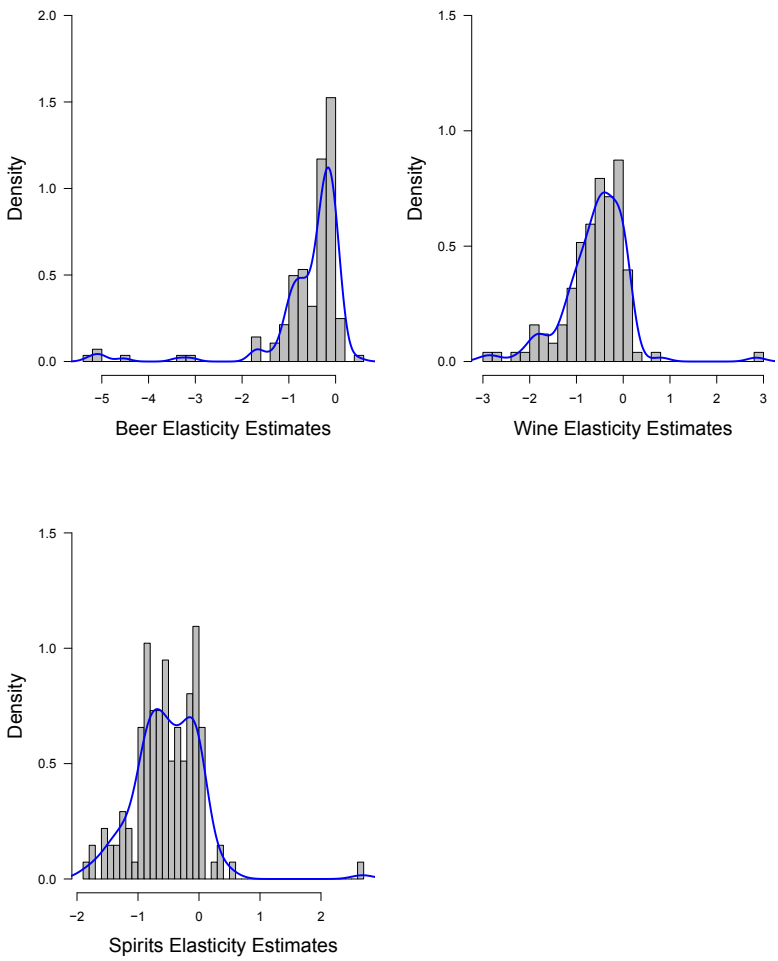
Figure 4.3: Country dispersion



In the literature for price elasticity of alcohol we evidence mostly data from

the high income countries. Our data confirms this, since most of the data originates from countries from the Anglosphere, that is 60% data from USA, UK, Canada, Australia and New Zealand together[1]. Russia[2] and Scandinavian countries account about the same, around 12% of the data each. Remaining European countries around 7% and Japan - 1.5%. The scarce data for low and medium income countries is more than obvious, since they account only for around 8% of the dataset, but we were still able to extract some data, which is more than any other previous meta-analyses on this topic. Figure 4.3 shows us visually how the data are distributed on country level. It is more than clear which countries dominate in the dataset.

Figure 4.4: Alcohol elasticity distribution



Before we move to the next chapter, we want to make one more visual

[1]The exact percentage distribution per country, could be found in Appendix A
[2]Estimates came from only one study - Goryakin *et al.* (2015)

check, using histograms and kernel densities, so we examine how the data are distributed and check for potential outliers, see Figure 4.4. In all three cases the data is highly concentrated on the left side, therefore implying that mostly negative estimates are reported. If this is due to the publication bias, then the true effect is exaggerated on the negative scale. If we do not consider the outliers it could be said that beer and wine follow a normal distribution, whereas spirits seem to be a bimodel, with two means - one inelastic, close to zero, and the second one close to -0.8. This could be also a result of the heterogeneity of the data. For example estimates based on daily data are perfectly inelastic, whereas monthly data exhibit elasticity of -0.7. However, whether this differences are fundamental or some of the variables are correlated, we would be able to explore more categorically in Chapter 6, where we would closely examine 23 variables that might contribute to the heterogeneity. Beer distribution seems to be very much skewed to the left side, but that is also due to some outliers, which are visible on the high negative scale around -5. We assign these estimates to Bray *et al.* (2009), which are obviously outliers. Bray *et al.* (2009) estimated the own-price elasticity for different beer packages (-six, -twelve and -twenty-four pack), which could be considered as subcategory in the group of beers. More subcategories also means more substitutes for a beverage not only across different alcohol types, but also within the group, therefore a higher price elasticity. Beer estimates compiled from Brey, 2009 were confirmed to be outliers when we checked for influential studies using the Baujat plot.[3], which justified their removal from the dataset.

[3]The Baujat plot is a diagnostic plot, that is used to detect and remove extreme effect sizes (outliers) in meta-analysis. We checked for influential studies to the random effect estimates. See figure A.1 in the Appendix A

Chapter 5

Publication Bias

Alcohol has been considered to be a normal good, where the expected price elasticity would be negative, following the "demand law" - the higher the price of alcohol, the lower quantity demanded. How people respond to price changes, will determine the price elasticity of the goods considered. The empirical literature found out that the demand for alcohol has always a negative elasticity, mostly evaluated to be quite inelastic and in average around -0.5, for all alcohol (Gallet 2007; Wagenaar 2010; Nelson 2013). To put this in perspective, it means that increase of alcohol prices by 10% would lead to a decrease of demand by 5%. Likewise, the previous meta-analyses conducted on this topic, always reported the lowest price elasticity for beer across all beverages. After we remove the outliers, our beer estimates go lower to -0.41, which is still in the average, if we compare it to the means reported in the previous analyses, that is -0.32 to -0.46, with the highest average being reported by Wagenaar (2010). As for wine and spirits, they do not change significantly, and are -0.59 for wine and -0.54 for spirits, which makes them a bit less elastic then the reported estimates in the counterpart meta-analyses -0.57 to -0.7, for wine, highest mean estimate reported by Fogarty (2010) and for spirits moving in the range of -0.59 to -0.8, with the largest average reported by Wagenaar (2010).

Nevertheless, one should be careful when interpreting the arithmetic simple mean, since the underlying effect might be driven by some imprecise studies. To correct for this we weight the estimates by the inverse of theirs standard errors, where more weight is given to more precise studies. The weighted mean reflects the relative importance of each observation, therefore it is more informative than the simple mean. One other advantage to these kind of weights is also that they accommodate for heteroscedasticity. Derived weighted mean in our

sample is -0.25 for beer, -0.3 for wine and -0.27 for spirits, which is almost twice the simple mean. This insinuates indeed that our arithmetic mean was driven by some large and imprecise studies.

Although the negative estimates are apparently dominant in this topic, it is also not implausible to believe that positive estimates could arise as well. That could be seen for example mostly with some high quality brands of wine and spirits, where people will buy this type of alcohol even if price increases. This kind of behavior is not untypical for the high income countries, where no budget constrains limitation is imposed (Pierani & Tiezzi 2009), but more interestingly, it is becoming also a trend in the rising economies, where expensive alcohol has been seen as a luxury good and a status symbol. For example in Thailand, the own-price elasticity for imported wine goes as positive high as 2.84, since the wealthy individuals believe that the more expensive the better the wine is (French 2016).

And yet, we do not see many positive estimates reported in the literature for the alcohol demand. Here, the question arises, if this is caused by the presence of publication bias. If many positive imprecise estimates are discarded, but many large negative estimates are reported, an upward bias toward the negative estimates arises in the literature. Authors mostly publish estimates that are statistically significant or/and with the expected "correct" sign. Therefore, if publication bias is present we would be missing estimates with the positive sign and higher standard error. In that case we would be dealing with a biased set of published estimates and reported mean that reflects that bias (Borenstein *et al.* 2011).

Publication bias or the "file drawer problem", where unpublished, insignificant studies with unanticipated outcomes are just filling the cabinets, has been one of the major concerns to the meta-analysts (Rosenthal 1979). Thornton & Lee (2000) assigned the origin of raising awareness for the existence of publication bias to the year 1956, when the editor of the Journal of Abnormal Social Psychology indicated that studies with unexpected outcomes were less likely to be published in his journal. They also present a nice survey of the literature and register more reasons why publication bias arises. The intention from the author to publish only significant studies sometimes could be justified, because if they submit studies with insignificant or counterintuitive outcomes, the journal editors might reject the papers. This makes the editors and the readers biased against the insignificant studies, since they consider them to be of a lesser interest. A source of funding could also play an important role, as

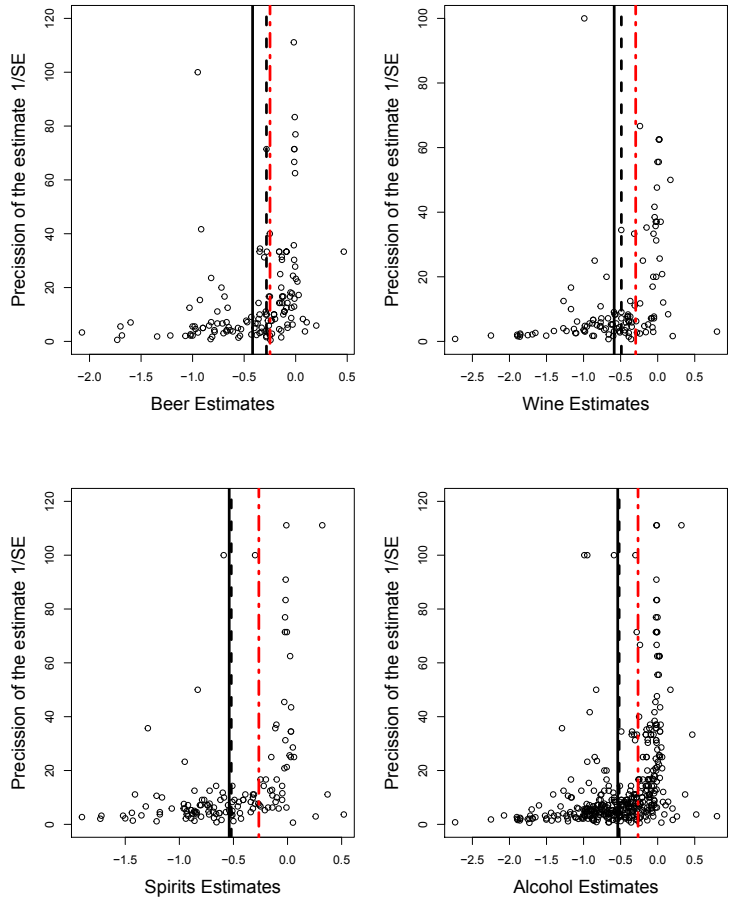
authors seek for outcomes that will mainly comply with the funder's expectations. Such publication or selection biases make empirical effects to exaggerate the arithmetic mean. To address the issue of the publication bias, we rely on a meta-analysis as a methodology that not only identifies the publication bias, but also corrects for it (Stanley 2005).

Card & Krueger (1995) were the first to model publication bias explicitly. But since then, statistical methods to address the issue of publication bias have been increasing constantly. As Egger *et al.* (1997) indicates, even though more methodological research would be required, the critical examination for the presence of publication bias should be considered a routine procedure.

A standard method for detecting publication bias is a funnel graph. It has been extensively used in recent meta-analyses (Nelson 2013; Havranek & Irsova 2017; Gechert *et al.* 2020). By plotting the reported elasticities against their standard error or precisions (the inverse of the standard errors), we can visually examine and detect the presence of publication bias. In absence of publication bias, the plot should resemble an inverted symmetrical funnel and the most precise estimates will be scattered around the mean underlying effect. As the precision decreases, the estimates will be more dispersed, forming a symmetrical "funnel-shaped" plot. The inverted funnel shape is defined by the predictable heteroscedasticity, since small studies will probably have large standard errors, hence less precision, and therefore will be found at the bottom of the graph, where the plot will be also more spread out, compared to its top (Stanley 2005). This also means that if no publication bias is present, there would be no relationship between standard error and the effect size. If on the other hand, the funnel plot is asymmetrical, that would be the first sign for possible publication bias. The more pronounced the asymmetry, the more likely is the existence of the publication bias. In that case we would have a statistically significant relationship between the standard error and the estimates, since then the smaller studies that found effects in one direction would be more likely to get published (Egger *et al.* 1997; Stanley & Doucouliagos 2012).

In the figure 5.1, we have displayed the funnel plots for all three beverages and also one plot for all estimates together. The first thing that could be spotted right away is their asymmetry across each beverage and alcohol generally. Positive estimates are almost missing, and the plots are skewed to the left, indicating a negative publication bias or biased selection for the "right" sign. The most precise estimates are being concentrated on the upper part of the graphs and closely scattered around or close to the zero, which might suggest

Figure 5.1: Positive estimates of the elasticity are underreported



Notes: In the absence of publication bias the estimates should be symmetrically distributed around the hypothetical true effect. The lower right plot represents the estimates from all beverages put together. The solid line represents the arithmetic mean estimate, dashed line the median and the two-dashed line represents the weighted mean by the inverse of the standard error.

that the demand for alcohol might be perfectly inelastic. The position of the mean suggests that in all of the cases the mean was overestimated and we were dealing with negatively biased arithmetic mean. Therefore we conclude that the authors indeed had preferences in reporting the expected "true" sign, but we cannot confirm that they were avoiding insignificant studies, since in that case plots would be hollow, less dense and empty around the zero, for missing estimates with little precision. But for none of the plots this could be confirmed. The plots also look very similar, which might suggest that the estimates do not differ significantly across beverages.

Funnel plots can be helpful in identifying possible publication bias, however it should be considered only as an informal method, since it does not have a

significant statistical power. Inspecting graphs could be always a subject of subjective assessment, therefore more objective statistical tests are needed. A researcher should be also careful when interpreting the funnel plots, since skewed plot might indicate publication bias but they could also be result of underlying heterogeneity (Stanley 2005). We have dedicated the next chapter to the heterogeneity.

To assess and correct the publication bias, we would need more formal statistical tests as the funnel plots. Since the publication bias is consistent with the findings of a correlation between the estimates and their standard errors, in that case the summary statistics and the standard errors would be biased. When there is no bias, the ratio of the estimate to its standard error should follow a t-distribution and the effect size estimates and the standard errors are independent. This association could be represented with the following regression-based test (Card & Krueger 1995; Stanley & Doucouliagos 2012):

$$\hat{est}_{ij} = \beta_0 + \beta_1 SE(\hat{est}_{ij}) + \upsilon_{ij} \tag{5.1}$$

where $\hat{est}_{ij}$ is the i-th estimate of the reported alcohol elasticity in the j-th study, $SE(\hat{est}_{ij})$ are the reported standard errors of the alcohol estimates, β_0 is the mean elasticity corrected for the potential bias, β_1 measures the extent and the direction of the publication bias, and the error term is a normal disturbance term. In absence of selection, observed effect should be independent of standard errors, therefore should vary randomly around the true effect estimate β_0. The coefficient on the standard error measures publication bias and can be thought of as a test of the asymmetry of the funnel plot.

In Table 5.1, we report the results of several specifications, based on the equation 5.1. We cluster standard errors at study level, since estimates reported in the same study are unlikely to be independent (Gechert *et al.* 2020). For all three beverages and total alcohol the intercept (the mean elasticity corrected for bias) and the coefficient on the standard error (publication bias) are negative and under some specifications highly significant. Applying equation 5.1 confirms the negative bias what we also assumed from the funnel graphs. The first column of Table 5.1 reports a simple OLS regression. All the estimates are highly significant. The price elasticity of alcohol, after correcting for publication bias drops for around a 0.1 for beer and wine, that is from -0.418 to -0.304 and from -0.54 to -0.418 respectively. Whereas for wine the difference is a little higher, or 0.26 falling from -0.587 to -0.322 and indicating that the wine

arithmetic average was biased the most. In the next two columns we applied two weighting schemes. In the second column, we weight the equation by the inverse of the standard error as an indicator for precision and also as a mean to capture heteroscedasticity. Application of the precision weights indicates a much stronger estimated bias, resulting in even smaller estimates, that are somewhere in the range from -0.132 to -0.172 across all beverages. These findings are also closer to what the top part of the funnel graphs were suggesting, true effect around 0 or -0.1. The estimates also differ by -0.1 point compared to the weighted mean. Even though under this specification the publication bias variable is highly significant across all the beverages, only the beer coefficient or the estimate beyond bias resulted to be significant at 10% level. As follows, in the third column we weight the estimates by the number of a Google Scholar citations that a study receives each year (Havranek & Irsova 2017). This way, more weight has been given to the highly-cited papers. Estimates and coefficients are significant for all beverages. The estimated mean coefficient decreases almost in the same manner as in the case of OLS, implying alcohol price elasticity to be around -0.3 for all beverages. Although we deal with relatively inelastic values, the presence of the publication bias across all beverages is obvious. Mutual also for all three specifications is that the arithmetic mean for wine was biased the most, exhibiting the highest difference between the arithmetic mean and the mean beyond bias. In absolute values, spirits estimate records the highest elasticity of them all, as we can see in the specification under OLS, where the corrected mean for bias is -0.418.

In the field of price elasticity of alcohol demand, the question of publication bias has not being assigned enough attention. Fogarty (2010) for example acknowledged the presence of a moderate publication bias in the case of beer estimates, but he did not correct for it, whereas Nelson (2013) was the first to not only confirm but also to correct for it in his meta-analysis. His findings comply with ours that there is a negative bias in literature, but he got to a slightly different outcome in the magnitude of the estimates. Namely he reported a precision-effect test(PET) estimates to be -0.172, -0.228 and -0.388 for beer, wine and spirits, respectively and for alcohol -0.316. In this case beer is the beverage that is the most inelastic, which might be more in compliance literature, then wine, followed by spirits. Under precision, we arrived to the same estimate for beer -0.172, but our estimates for wine -0.162, spirits -0.132 and alcohol in general -0.155 are apparently less elastic when compared to Nelsons', which suggests that price elasticities for wine and spirits have decreased

Table 5.1: Asymmetry funnel test suggest publication bias

		OLS	Precision	Citations
Beer	SE(publication bias)	-0.577**	-1.249***	-0.558*
		(0.258)	(0.446)	(0.315)
	Constant(effect beyond bias)	-0.304***	-0.172*	-0.329***
		(0.078)	(0.101)	(0.088)
	Studies	66	66	64
	Observations	134	134	129
Wine	SE(publication bias)	-1.112***	-1.785***	-1.189***
		(0.420)	(0.544)	(0.444)
	Constant(effect beyond bias)	-0.322***	-0.162	-0.291***
		(0.116)	(0.139)	(0.100)
	Studies	58	58	57
	Observations	122	122	119
Spirits	SE(publication bias)	-0.631	-2.114***	-1.070***
		(0.384)	(0.512)	(0.342)
	Constant(effect beyond bias)	-0,418***	-0,132	-0.326***
		(0.109)	(0.106)	(0.077)
	Studies	66	66	64
	Observations	135	135	130
Alcohol All	SE(publication bias)	-0.768***	-1.718***	-0.881***
		(0.270)	(0.434)	(0.326)
	Constant(effect beyond bias)	-0.353***	-0.155	-0.327***
		(0.090)	(0.107)	(0.800)
	Studies	77	77	75
	Observations	391	391	378

Notes: In the table are presented the results of the regression $\hat{est}_{ij} = \beta_0 + \beta_1 SE(\hat{est}_{ij}) + v_{ij}$. $\hat{est}_{ij}$ and $SE(\hat{est}_{ij})$ are the i-th estimates of alcohol elasticity and their standard errors reported in the j-th study. The standard errors of the regression parameters are clustered at study level. OLS = ordinary least squares, Precision = the inverse of the standard error of the reported estimate's is used as the weight, Citations = the number of Google Scholar citations received per year is taken as the weight. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

over time. Even though estimates for wine, spirits and alcohol in general were not significant under precision, the estimates follow the same pattern as in the other regression specifications. One other meta-analysis that considered the publication bias, is the one conducted by Fanta (2014) in his bachelor thesis. The corrected means for bias in his estimation, were -0.16 for beer, -0.02 for wine and -0.035 for spirits, but only the estimates for beer were found to be significant.

Altogether, we found a significant publication bias across all alcohol beverages and the mean estimate for alcohol in general lies between -0.35 and -0.15. Beer price elasticities seems to not change much over time and it is the beverage where the estimates were found significant across all specification. Whereas elasticities for wine and spirits have dropped and are less elastic than what the literature reports. Under all specification the price estimates for different beverages are quite close to each other, however whether there is no structural difference between them will be examined in more details in the next chapter.

5.1 A "Stem-based" bias correction method

The funnel asymmetry test explained above is intuitive and performs well under the assumption that the publication selection forms a linear function to the standard error. To assess the bias under the assumption of nonlinearity, we would apply one new non-parametric method, recently created by Furukawa (2019). Various existing bias correction methods anticipate a specific selection process, whether that be the size of the estimates, their significance, or even both. On the other hand, this model, being totally data-dependent does not rely on the assumption for a specific selection process. The model classifies as generally conservative bias correction method that relies on the common prediction that the most precise studies are less biased. This proposition shows that the bias is decreasing as the study precision increases, and under some conditions, as studies become infinitely precise, the bias will approach zero. Since the model is using only the estimates from the studies with the highest precision, it corresponds to the "stem" of the "funnel plot", hence the name "stem-based" bias correction method. This model could be also seen as an extension to Stanley *et al.* (2010), where they suggest using only 10% of the most precise estimates. The model tries to optimize over the bias-variance trade-off, by choosing the right number of "precise" studies - n_{stem}.

To choose the optimal n_{stem} number, for the most precise studies to be included,

Table 5.2: Stem-based technique on the publication bias

	Estimate	**se**	**n_stem**	**% info used**
Beer	-0.168	0.142	6	0.056
Wine	-0.507	0.049	122	1
Spirits	0.0033	0.205	3	0.028
Alcohol	-0.164	0.176	4	0.013

Notes: Estimate refer to the true effect or the "corrected" bias estimate, whereas SE it is the standard error to the estimates. *n_stem* is the optimal number of the precise studies that should be included in the model. The last column % info used, is just a reference for how much information did the estimation used from the total data.

Furukawa (2019), suggests minimizing the mean squared error by solving for the following:

$$\min_{n} MSE(n) = Bias^2(n) + Var(n) \tag{5.2}$$

Defining the right n_{stem}, is highly important, since if we include just few studies we would be dealing with high variance, loosing efficiency, and as we include more studies the variance will decrease. But as we have mentioned, the idea is not to include all the studies, since in that case we will be again dealing with an upward bias. To solve this equation or to minimize the trade-off between the variance and the bias, we need to apply a non-parametric estimation techniques that uses two algorithms. The first one (inner algorithm), computes the bias-corrected mean, by approximating the value of the squared precision and the second algorithm (outer algorithm) computes the implied variance, ensuring that the implied and assumed variance are consistent with one another.[1]

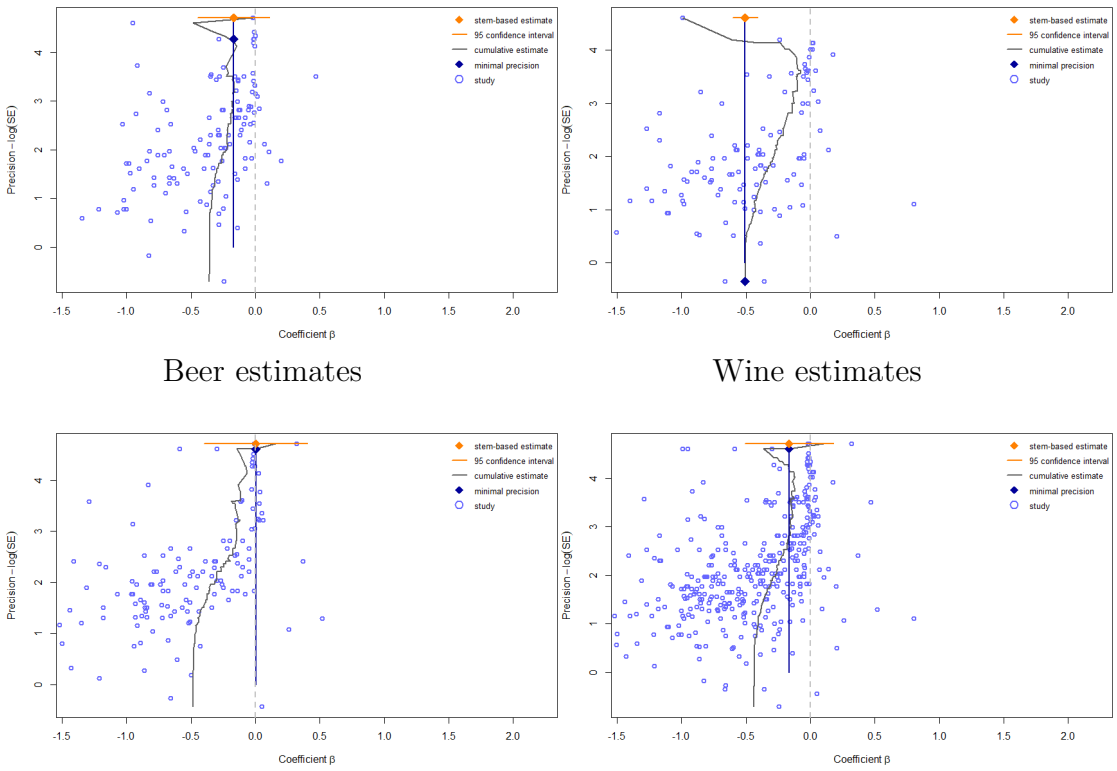
The results in Table 5.2, represents the simulations of the stem-based method applied to our dataset. As we can see in the case of wine the algorithm does not converge and it uses all the studies, hence the estimate is not corrected for its bias. The mean elasticity corrected for publication bias for beer and alcohol are almost the same as the estimates from the asymmetry funnel test, when weighted for precision, see Table 5.1. Spirits on the other hand are perfectly inelastic. The model utilizes relatively small % of the total information contained

[1]The estimation steps for a "stem-based" method and how the bias is calculated is closely explained in Appendix B. The author also provided a free R code to implement the model, which is available under $https://github.com/Chishio318/stem-based_method$

in the data - 5.6%, 2.8% and 1.3%, hence the small number of n_{stem} estimates. The small number of studies explains also the higher standard error of the estimates. When interpreting the outcomes from this simulation, one should also consider that we are talking about a relatively new method that might not be so robust. However, under the assumption of nonlinearity, we again confirmed that the arithmetic mean of alcohol price elasticity is exaggerated by a negative bias.

The estimates of stem-based method can be visually represented with a funnel plots as in the Figure 5.2. The top orange diamond represents the stem-based estimate or the "correct" bias estimate, whereas the blue diamond a bit below is the threshold for a minimal precision. n_{stem} corresponds to the number of precise studies that are above the blue diamond. As we could see in the Table 5.2, this corresponds to 6 studies or 5.6% of the total sample.

Figure 5.2: Funnel plots for stem-based method



Notes: The orange diamond (lighter in grayscale) at the top indicates the stem-based estimates of the mean elasticity beyond bias, along with the orange line that represents the 95% confidence interval. The dashed grey line (lighter in greyscale) is the estimate under various $n_{stem} \in 1, ..., N$. The blue diamond (darker in grayscale) stands for the level of precision for the inclusion. This is the threshold for study inclusion, since every precise study that is above this diamond represents the stem-based estimate.

Chapter 6

Heterogeneity

Alcohol price elasticity is heterogeneous across different studies, influenced by different aspects attributed to the way the authors were collecting data. Determining which factors explain the heterogeneity the most is of importance especially to the policy makers, since it helps them sculpture an efficient policy against the extensive use of alcohol. Therefore, apart from the elasticity estimates and their standard errors, we collected 23 variables from 78 studies, that should be regrouped, according to some common characteristics. Since many of these additional study attributes can explain the variation in the estimates, we need to control for them, in order to understand what is causing the heterogeneity. First, we divide the variables into seven groups. The first group contains the type of beverages we examine the price elasticity for, that is beer, wine and spirits. Second, we control for estimation approaches. Third, we distinguish between the data originating from different countries. Fourth, we include dummy variables that control for data frequency. Fifth, considers a different demand equation specification. Sixth, summarizes data according to the number of years used in the data, whether the alcohol is imported or not, short run or long run estimates and if addiction was considered when deriving the estimates. And the last group of variables includes information on the publication characteristics of the study. Variables are summarized in Table 6.1.

6.1 Variables and estimation

Type of beverages The main three beverages we are examining in this thesis as a representative of alcohol demand are beer, wine and spirits. We do not

divide them in separate models, even though we are aware that due to our decision we might lose some information, but instead we set beer to be our reference category. Our choice to run the different beverages under one model is justified also by the findings in Chapter 5, where the estimates after correcting for publication bias are pretty close to each other, suggesting that they might not be structurally different from each other. The choice to consider beer estimates as base is purely random, since all the beverages are almost evenly distributed, that is 35% beer estimates, 31% for wine and 34% for spirits. We include dummy variable equal to one to attribute to the study containing the estimate for that particular beverage.

Estimation approaches We also include dummy equal to one when the reported estimates are very disaggregated for potential estimation approaches differences. We are interested to estimate whether time-series, cross-sectional or panel data approaches differ significantly and to what extend could explain the data heterogeneity. System-wide approaches are of particular interest, since as the vast literature indicates these approaches have gained popularity and have an increasing application (Aepli 2014; Janda *et al.* 2010; Laković *et al.* 2019). Around 44% of our dataset is assigned to system-wide approaches.[1]

Countries data The assumption that the heterogeneity of the data could be explained by the cross-country differences has been explored further by setting the countries of the Anglosphere as a reference variable, since these estimates account for 60% of the data. We are interested whether developed countries will not differ significantly from the reference category and to what extent the LMI-countries contribute to the total variation of the estimates. Considering the increased alcohol consumption trends in the developing countries, it is important to inspect to what extent these data are significant and could explain the data heterogeneity. However, literature on alcohol price elasticities for the developing countries is scarce, since most of the studies include data only from the high income countries.

Frequency Regarding data frequency, estimates based on annual data is our baseline category, employed to 60% of the data. For the use of quarterly,

[1]System-wide utility based approach is more complex specification that represents a system of demand equations. AIDS = Almost Ideal Demand System. All system-wide approaches are coded as one group.

Table 6.1: Description of explanatory variables

Variables	Description	Mean	SE
Type of beverages			
Beer	= 1 if the estimates refer to beer (Beer is the reference category)	0.34	0.48
Wine	= 1 if the estimates refer to wine	0.31	0.46
Spirits	= 1 if the estimates refer to spirits	0.35	0.48
Estimation approaches			
Time-series	= 1 if time-series approaches were applied	0.10	0.30
Cross-sectional	= 1 if cross-sectional approaches were applied	0.07	0.26
Panel	= 1 if panel data approaches were considered	0.28	0.45
System-wide	= 1 if system-wide approach was applied in the estimation (Rotterdam, AIDS, or a hybrid of these two)	0.44	0.50
Countries data			
Anglosphere	=1 if the estimates refers to data from Australia, Canada, New Zealand, UK, USA (Anglosphere countries are taken as reference category)	0.60	0.49
Northern Europe	= 1 if the estimate is for Denmark, Finland, Norway, Sweden	0.12	0.33
Western Europe	= 1 if the estimate is for France, Switzerland, Germany, Austria, Belgium, The Netherlands, Czechia	0.05	0.22
Southern Europe	= 1 if the estimate is for Cyprus, Greece, Portugal, Italy	0.02	0.12
Japan	= 1 if the estimates are for Japan	0.02	0.12
LMIC	= 1 if the estimate is for Chile, India, Montenegro, Taiwan, Thailand, Vietnam	0.08	0.27
Frequency			
Annual	= 1 if the data frequency is annual (estimates based on the annual data have been taken as reference category)	0.63	0.48
Quarterly	= 1 if the data frequency is quarterly	0.09	0.29
Monthly	= 1 if the data frequency is monthly	0.10	0.30
Daily	= 1 if the data frequency is daily	0.18	0.38
Demand specification			
Unconditional	= 1 if the budget share is unconditional	0.38	0.48
Hicksian	= 1 if the demand equation is Hicksian (compensated)	0.63	0.48

Continued on the next page

Table 6.1: Description of explanatory variables(continued)

Variables	Description	Mean	SE
Data characteristics			
Number of years	The logarithm of the number of years in the data	2.66	0.92
Import	= 1 the elasticity is estimated on imported beverages	0.05	0.22
Long Run	= 1 if the estimates is taken from long-run specification (short-run estimates are the reference category)	0.08	0.27
Addiction	= 1 if addiction is considered	0.14	0.35
Publication			
Publication year	The year of publication of the study minus 1949, the year when the oldest paper in our dataset was published	51.42	13.58
Citations	The number of per-year citations of the study in Google Scholar, since the publication year	2.61	2.38
Journal impact	The simple RePEc impact factor of the outlet(collected in April, 2020)	6.02	7.63

monthly and daily data we include dummy variables.

Demand specification This variable is generated according to the type of demand function considered when computing the demand price elasticity. We identify Hicksian (compensated) and Marshallian (uncompensated) demand functions. When we are interested in the own-price elasticity of a good i, holding other prices and the real income constant, then we consider the Hicksian or compensated demand function. It is a demand function that holds utility fixed, therefore when price of a good i increases it has to be compensated with a less costly ones in order to maintain the same level of utility. This compensation effect caused by the price changes is known as substitution effect. Whereas the Marshallian (uncompensated) demand function maximizes utility and deals with how price change will affect the demand for the good i, where the money income is hold constant. Therefore in a situation where prices drop, even though the nominal wealth remains the same, the consumer will be better off. Hence the uncompensated demand function reflects not only the substitution, but also the income effect. Both Hicksian and Marshallian elasticities contain information that would be of value to the policy makers to understand the demand response to price changes. For a normal good, as alcohol is considered to be, the Hicksian (compensated) demand function is

less responsive to price changes then the Marshallian (uncompensated) demand function (Fogarty 2010).

The second set of variables in this group accounts for conditional and unconditional price elasticities. Unconditional demand equation is derived from the general utility function for all n goods and all n prices of total expenditure, whereas the conditional demand equation considers only one group of goods i.e. the conditional alcohol price elasticity will concern only the alcohol beverages (Selvanathan & Selvanathan 2007).

Data characteristics We have a dataset that goes over a long spectrum of time, where some studies consider estimates only for one year (Araya & Paraje 2018; Kumar 2017) and then some other extend the dataset up to 64 years (Prest 1949). Over this range of data, we would be interested to check to what extent the variable number of years impacts the elasticity estimates. Import data are distinguished to estimates that are computed on the price elasticity on domestic alcohol beverages and to price elasticity estimates from imported alcohol. It is an important variable since if influential it could distort the domestic alcohol production significantly. Another important aspect of estimating the elasticity is whether the estimate refers to a short-run or a long-run elasticity. Short-run estimates are the reference category, since they contribute to over 90% in our dataset, suggesting at the same time that the authors apparently prefer the short-run elasticity estimates. Under addiction are considered estimates for the demand elasticity that account for heavy and addictive drinkers. We are particularly interested in the price responsiveness of this sub-group category, since these are the ones that contribute the most to the negative externalities of alcohol over-consumption.

Publication In this group of variables we control for publication characteristics of the studies. Firstly, we are interested if there is a publication trend in the elasticity estimates. Therefore we find the year when the study was firstly published and subtract the publication year of the oldest study in our dataset. Next, we want to capture the quality of the study, hence we include variable citations that controls for the average number of citation per year in Google Scholar, since the publication year. To control for the different quality of the publication outlet, we include the simple RePEc impact factor.[2]

[2]RePEc - Research Papers in Economics is a public-access database that promotes scholarly communication in economics and related disciplines. The database contains information

Heterogeneity has been routinely observed in the economics and social science researches. To investigate why different researchers generate different estimates of alcohol price elasticity, we employ Bayesian model averaging (BMA) - a method that accounts for model uncertainty in linear regression models (Raftery *et al.* 1997). Previous analyses have addressed heterogeneity as well, but this is the first meta-analysis on the alcohol price elasticity to apply this method. If we estimate the model using OLS, by including all 23 explanatory variables, the regression will probably contain many redundant variables, which will distort the perception on the alcohol price sensitivity and we will not know which of the variables we should exclude. Selecting one model and making inference conditional on that model, ignores the uncertainty involved in model selection (Kass & Raftery 1995). Bayesian model averaging goes beyond the problem of model selection, combining estimation and prediction that generates a straightforward model choice criteria and less risky predictions. The model has an extensive application in literature that could be observed in the work of Fragoso *et al.* (2018). They present how the model developed by examining 587 articles where BMA was applied for the publication period between 1996 and 2014.

The advantage of BMA is that it accounts for as many aspects as we want to include, generating a pairwise possible subsets. In our case there would be 2^{23} possible combination. For each model BMA assigns a weight, which is called the posterior model probability (PMP) and captures how well the model fits the data. PMP could be compared to the adjusted R^2 in the frequentist econometrics. Regression coefficients are derived on a weighted average over all possible combinations of predictors, where the weights are the posterior model probabilities. Then for each variable a posterior inclusion probability (PIP) is computed, which is the sum of the posterior model probabilities of all the models in which the variable is included. In other words, the posterior inclusion probability actually specifies how likely it is that the variable should be included in the true model. The popularity of the BMA goes hand in hand with the popularization of the Markov chain Monte Carlo method (MCMC) software that is integrated with the R Statistical Software that made the application of the Bayesian inference available to a broad audience. Namely if we were to estimate all the 2^{23} possible models it would take us a very extensive amount of

on more than 585.000 items, including individual professionals, institutions, working papers, articles, books and chapters and software descriptions and programs. A simple impact factor is a computing a ratio of total citations by the number of items in the series. Retrieved from http://repec.org/.

time, months even. Whereas when the MCMC method is applied it generates a process that moves through the models with the highest posterior probabilities and delivers an output in just a few minutes to couple of hours, depending on the dataset and the number of iteration given in the model specification.

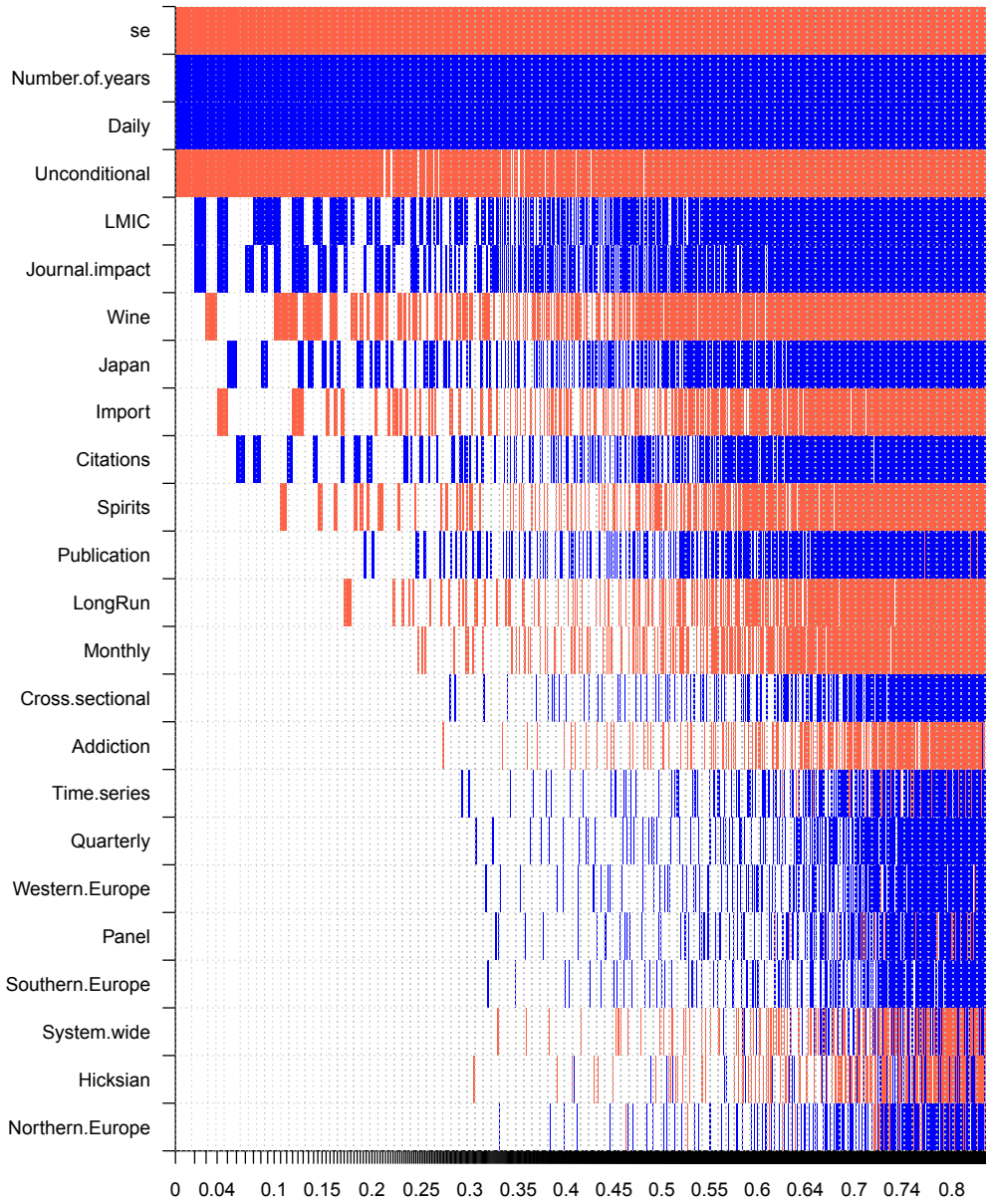
6.2 Results

Bayesian framework allows us to deal with both model and parameter uncertainty, providing a coherent statistical framework, where inference is based on all models, averaged by their posterior probabilities. Therefore there is no need for us to choose any particular model or disregard any variables. Based on the information collected from the empirical studies, BMA identifies the set of variables that explain the heterogeneity and corrects for potential bias or misspecification biases (Havranek & Irsova 2017). In order to obtain posterior distribution, first we need to specify prior distribution on the model parameters, or as it is called Zellner's g prior. In our baseline model we use a "unit information prior" (UIP) that sets g = N, meaning that the same information is attributed to the prior as it is contained in one observation (Zeugner *et al.* 2015). Second, we determine the prior probability of each model and we choose the uniform model prior, which gives each model the same prior probability. These priors derive the best predictive performance (Eicher *et al.* 2011). The Bayesian framework gives the BMA user the flexibility to modify the prior setup as desired, and sometimes a different choice of priors might influence our results.

In Figure 6.1 we can visually examine our results. Each column represents an individual regression model and the width of the columns indicates the posterior model probability. The rows represent the individual variables sorted by posterior inclusion probability in descending order. Blue (darker in grayscale) and red (lighter in grayscale) colors indicates that the variable is included in the model and empty cell means that it is not. Blue color also stands for positive estimate and the red one for the negative ones. The cumulative posterior model probability is measured on the horizontal axis, which indicates that the best models will be shown on the left. Moreover we observe that the standard error and the first three variables are included in almost all regressed models.

The numerical results of the BMA are reported in the left-hand panel of Table 6.3. As a robustness check, next to it we represent the OLS estimates, but we include only those variables with posterior inclusion probability of at least

Figure 6.1: Model inclusion in Bayesian model averaging



Notes: The response variables is the estimate of the elasticity of alcohol demand. se = standard error, LMIC = low and medium income countries. Columns represent individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities; only the 5,000 best models are shown. Blue color (darker in greyscale) = the variable is included and the estimated sign is positive. Red color (lighter in greyscale) = the variable is included and the estimated sign is negative. No color = the variable is not included in the model. Numerical results on the BMA application are reported in Table 6.3. All the variables are described in details in Table 6.1

0.4. Above this threshold only six variables appear to drive the heterogeneity in the estimates. Very important is that the variable for the publication bias, the standard error of the estimate is also highly significant, with a posterior inclusion probability of 100%, which confirms that our results in the previous Section 5 remain robust and that the correlation between the estimates and standard errors is not driven by omitted variables(Gechert *et al.* 2020). Six other variables have a posterior inclusion probability, above 0.4. OLS estimates are pretty close in the magnitude to the corresponding BMA posterior mean and are all significant, with exclusion to LMIC. In Appendix C, Table C.1 we present an alternative "best practice" OLS model including only the variables with posterior inclusion probability above 0.8. The model might be to some extent a slightly better fit as all the variables are significant, however due to the scarce data the results might not be so robust. Namely, the variable LMIC attributes only to 8% of total data and yet has a posterior probability inclusion of almost 0.5, which is an indicator that these data may be drivers to the data heterogeneity.

As the literature and previous analyses suggest, we consider negative price elasticity when interpreting the posterior means compared to the reference category.

Type of beverages The posterior mean estimate suggest that beer is the least elastic type of alcohol beverage as literature suggests (Fogarty 2010; Nelson 2013; Gallet 2007). Estimates seem to be pretty close to each other, which confirms our assumption that the price elasticity for wine and spirits have decreased following the increased consumption pattern. Spirits estimate seems not to be structurally different than beer estimate, however we cannot confirm the same for wine, since it has PIP of 0.44 and seems to be significant in explaining the data variation. One possible explanation for this might be the heterogeneity in wine products itself, compared to that of beer and spirits. Pooling wine might not be an appropriate specification when modeling the demand for wine and probably a more disaggregated approach should be considered.

Estimation approaches In light of the increasing application of more complex estimation approaches, like the system-wide specification, the model suggests that even under the less complex estimation approaches the estimates

Table 6.3: What variables contribute to the heterogeneity the most

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of elasticity	Post.mean	Post.SD	PIP	Coef.	Std.er.	p-value
SE(publication bias)	-0.512	0.098	1.000	-0.456	0.232	0.054
Type of beverages						
Wine	-0.054	0.071	0.444	-0.101	0.048	0.039
Spirits	-0.021	0.049	0.199			
Estimation approaches						
Time-series	0.004	0.025	0.051			
Cross-sectional	0.007	0.038	0.059			
Panel	0.002	0.019	0.044			
System-wide	-0.001	0.012	0.039			
Countries data						
Northern Europe	0.001	0.013	0.032			
Western Europe	0.004	0.028	0.044			
Southern Europe	0.005	0.043	0.040			
Japan	0.124	0.204	0.328			
LMIC	0.113	0.133	0.494	0.219	0.166	0.193
Frequency						
Quarterly	0.003	0.022	0.046			
Monthly	-0.024	0.072	0.143			
Daily	0.389	0.076	1.000	0.434	0.080	0.000
Demand specification						
Unconditional	-0.129	0.071	0.849	-0.165	0.060	0.008
Hicksian	-0.001	0.012	0.035			
Data characteristics						
Number of years	0.140	0.029	1.000	0.148	0.036	0.000
Import	-0.051	0.102	0.252			
Long Run	-0.023	0.062	0.158			
Addiction	-0.003	0.021	0.051			
Publication						
Publication year	0.001	0.002	0.185			
Citations	0.005	0.011	0.248			
Journal impact	0.004	0.005	0.457	0.008	0.003	0.027
Constant	-0.857		1.0000	-0.860	0.149	0.000
Observations	391			391		

Notes: SD = standard deviation, PIP = posterior inclusion probability, LMIC = low and medium income countries. In the frequentest check we include only explanatory variables with PIP > 0.4. The standard error in the frequentest check (OLS) are clustered at the study level. All the variables are described in details in Table 6.1

will not differ. The magnitude of the posterior mean is very low, almost zero and none of the variables are significant nor contribute to the heterogeneity of the data.

Countries data Positive posterior means by all groups of countries suggest that the countries from the Anglosphere are more elastic. However the difference to European countries is very small and insignificant which indicates that the high income countries, Japan not considered, do not exhibit any different patterns to alcohol demand. On the other hand, estimates for Japan and LMIC seem to be less elastic, or if the reference country would have had inelastic price elasticity, then they might even exhibit positive estimates. Estimates for Japan, are however insignificant. More importantly is that the LMIC have posterior inclusion probability of almost 0.5, which is an important finding considering that the data for LMIC contributes only to 8% in the total dataset. In general data for the LMIC is scarce, therefore if these countries are drivers to the heterogeneity, it is highly important future researches to be directed more to these regions, where new evidence could better explain the reason for heterogeneity.

Frequency Under the assumption of negative estimates based on annual data, only the monthly data are more elastic, whereas the smallest estimates are the one based on a daily frequency. This might suggest that high frequency data are inelastic, which is in line with the findings in the previous studies (Fanta 2014; Gallet 2007). However it seems that none of the frequency data matters and only the daily frequency data are significant and have a decisive posterior inclusion probability. This is an important find since most of the data on price elasticities are attributed to annual data. However, collecting high frequency data could be expensive and time consuming, but in light what the model outcome also suggest, is that high frequency data should be more often considered when alcohol price elasticity demand has been estimated.

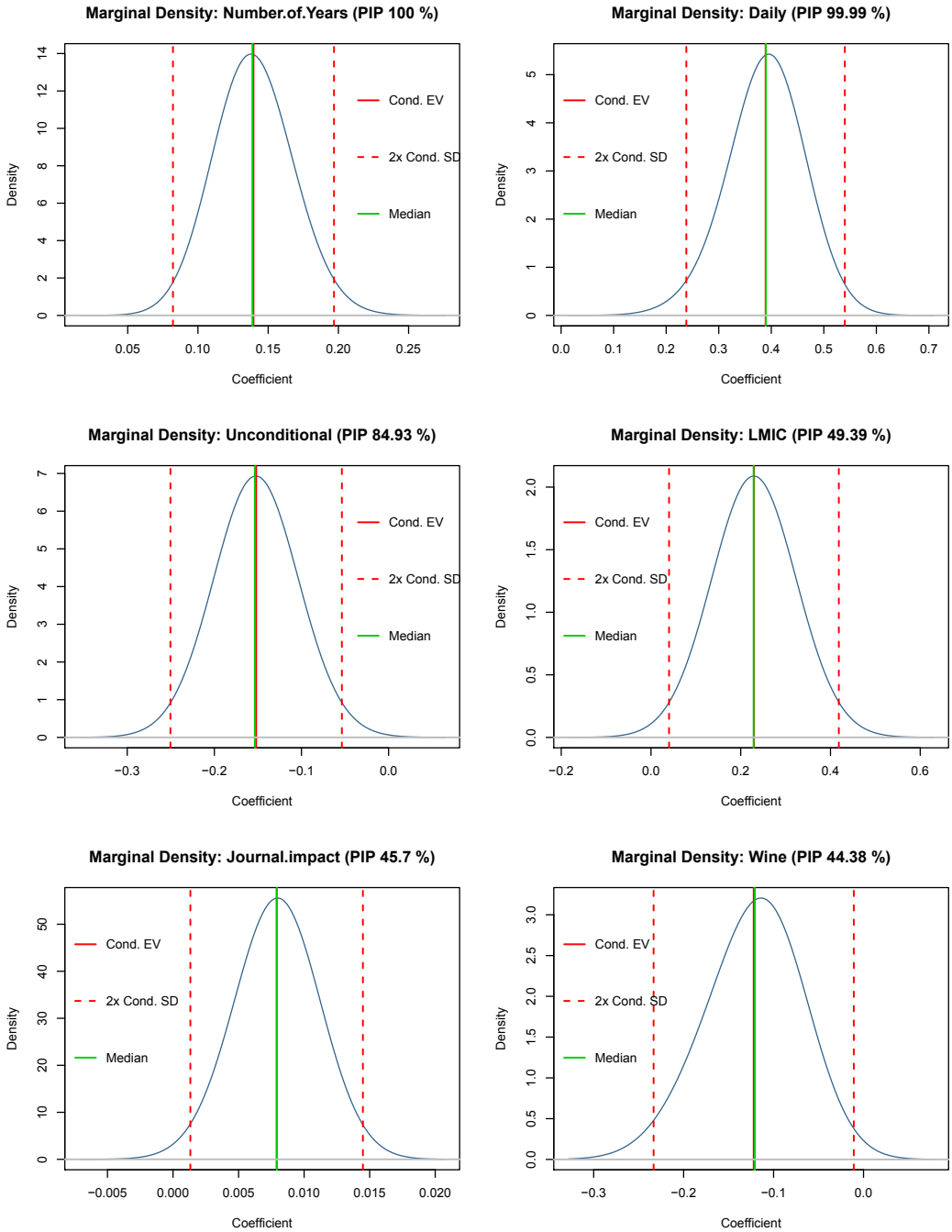
Demand function In this group we found unconditional demand elasticity to have strong PIP. The negative sign is in line with the literature suggesting that unconditional estimates will always exhibit higher price elasticity than the conditional estimates. Namely under the unconditional demand function, when price of good i changes, it is considered in variation to other goods. Having more substitutes explains the higher price elasticity. It is also variable that was

included in 85% of the posterior models, therefore a strong driver to heterogeneity of the data. On the other hand, the Hicksian or Marshallian demand function seems to not matter. They are neither significant nor different from each other. Fogarty (2010) suggests that Marshallian price estimates are by 25% higher than the Hicksian ones. However we do not find evidence for it. Such information would have implication to the policy makers, suggesting that they could pool estimates from the Hicksian and Marshallian demand function together, since pooling will no alter the estimates in any significant way. On the other hand, the unconditional price elasticities might be of greater interest, not only because they explain the data heterogeneity better, but also because policy makers are rather more interested in estimates that mirror the price responsiveness in consideration to the other goods Fogarty (2010).

Data specification Number of years in the data is one of the strongest variables in our model, that indicates that the longer the data the more important this variable becomes. This makes sense also in terms of the changing preferences of people throughout time. Longer data should catch more variation in people's behavior, however the estimates tend to be positive. Estimates from imported goods are more elastic, which is important information for sales strategies for alcohol stores. Namely if they want to organize a sale on some alcohol beverages, they might consider that people will be more sensitive to the price changes of imported goods. As for the policy makers they should tax imported goods with a higher rate than the domestic ones, so they could protects the domestic production more. But this variable contributes poorly to the heterogeneity of the data, therefore it is considered to be insignificant. People should adjust better to the price changes in a long run, which variable Long Run confirms. The short run elasticity is more inelastic then the long run Gallet (2007). However this is also not a significant variable. With estimation of variable addiction we join the group of economist that arrived to the conclusion that heavy drinkers are not responsive to the price changes (Ayyagari *et al.* 2013; Meier *et al.* 2010; Wagenaar *et al.* 2009). Even though this variable is not significant, it reflects how inefficient the taxation policy would be, since none of the fiscal measurements will affect this subgroup. Considering more non-fiscal instruments, might be a better solution.

Publication In this group it seems like the only variable that contributes to the heterogeneity is the Journal impact. Better papers also tend to publish

Figure 6.2: Posterior coefficient distributions



Notes: Plots depict the posterior density for the selected variables conditional on inclusion. Cond. EV = the posterior expected value, Cond SD = the posterior standard deviation and Median = median of the posterior distribution.

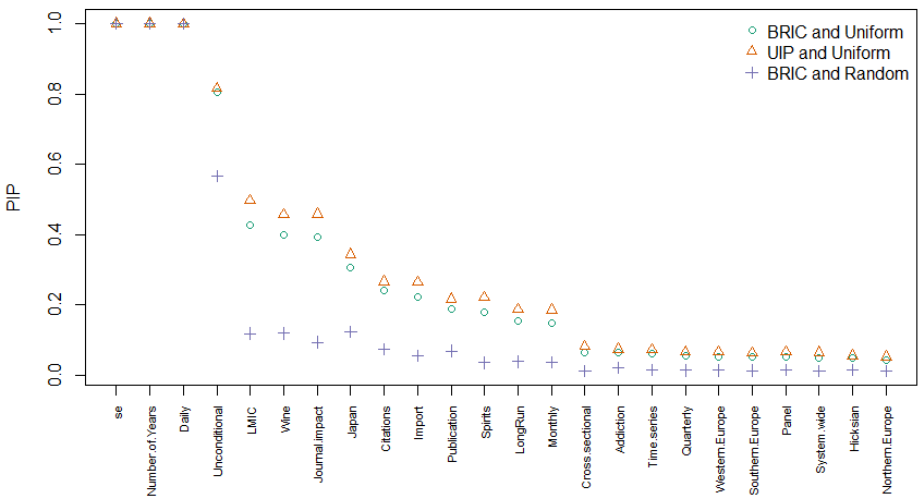
estimates that have a positive response to the price changes. Publication year, hence no trend in the publication, alongside with the citation of the papers does not seem to matter.

In Figure 6.2 we can see the posterior coefficient distribution for the selected variables. Each plot is a combination of the marginal posterior densities of the individual models where the corresponding variable has been included. Therefore the marginal posterior density could be interpreted as "conditional on inclusion" and could be calculated only for the top models (Zeugner *et al.* 2015).

Further more in Figure 6.3 we depict how the posterior inclusion probability changes when we use a different set of priors. Our baseline model was set to unit information prior (UIP) and uniform model prior. One other alternative to the unit information prior is the BRIC g-prior suggested by Fernandez *et al.* (2001), which sets the g-prior to $g = max(N, K^2)$, where K is the total number of covariates. And as an alternative to uniform model prior we might also consider the random beta-binomial model prior (Steel & Ley 2007), which implies that each model size has the same prior probability.

All three approaches are consistent on the variables with the strongest PIP of 100%. Under the combination of BRIC and random beta-binomial prior we see that the other variables have reduced PIP, however the ranking is kept the same, which indicates that under different prior combination and alternative thresholds we would have the same combination of variables in terms of importance.

Figure 6.3: Different priors settings



Chapter 7

Conclusion

Our analysis builds on several recent meta-analysis on alcohol price elasticity (Fogarty 2010; Fanta 2014). We extend the dataset to recent available data and at the end we examine 391 estimates for beer, wine or spirits elasticity reported altogether in 78 studies. We show that in the last 20 years drinking preferences have changed not only across different alcohol beverages but also across countries. Price elasticity of alcohol follows the inverse relationship to the volume of consumption and exhibits decreasing pattern for wine and spirits, as people tend to prefer them more over beer. Our data confirm this assumption and after we correct for the presence of publication bias, price elasticity for wine and spirits decrease from -0.5 to an average of -0.3. With the new evidence in hand, the price elasticity of the three main beverages differs now in a lower magnitude than the previous literature suggest, therefore we cannot say with certainty that beer remains to be the least elastic alcohol beverage of them all. Wine seems to be the beverage type that was biased the most, which was also confirmed under different specification of the funnel asymmetry regression test designed for publication bias correction.

Funnel asymmetry test performs well, when there is a linear relationship between the publication selection process (whether that be the size of the estimates or theirs significance) and the standard errors of the estimates. To examine the presence of publication bias under the assumption of nonlinearity we apply one non-parametric technique, recently created by Furokawa, 2019 - the “stem-based” method. Under this assumption literature seems to be even more biased and we derive to corrected mean of -0.16 in average for all alcohol beverages. As far as we know this is the first meta-analysis to confirm and correct for publication bias in the literature, by applying both liner and nonlinar

techniques.

To emphasize the effects of the data dispersion, we apply Bayesian model averaging, that accounts not only for the uncertainty in the parameters but also in the model. The model allows us to control for as many variables as we want to include and derives the "best" fitting model identifying the variables that contribute to the heterogeneity the most. We control for additional 23 aspects of the studies and arrive to the conclusion that the lengths of the data and high frequency data have strong contribution to the data variation. Our results also suggest that the demand function plays also an important role in explaining the data heterogeneity. Namely conditional and unconditional elasticity estimates should not be pooled together when important decision should be based on the price elasticity of alcohol. The standard error as a variable for the publication bias is also important, confirming that the publication bias is not result to some omitted variables. After correcting for publication bias, the estimates for the three main beverages got closer to each other, hence it is only natural to assume that they are not structurally different. However, the wine estimate seem to be different and wine should be considered rather as a separate group. This might be also justified by the fact that wine has many more subcategories, which could suggest higher variation within the categories and this is something that might be interesting to be considered for any future studies. The quality of the publication paper seems to also matter.

In terms of country dispersion we found evidence that low and medium income countries are important drivers to the price elasticity, which is an interesting evidence, considering that these group of countries exhibit increased alcohol consumption. Moreover the severity of alcohol over-consumption in these countries is stronger than in the high income countries. However our data on LMIC accounts only to 8% of the total data and yet it has posterior inclusion probability of almost 50%. We should be careful when interpreting these findings, since due to the limited sample size, our results might not be so robust. But for sure, these outputs are more than a certain indicator for the importance of the future studies to be more directed towards enriching the scarce literature on price elasticity on alcohol demand in these groups of countries. We do not find evidence that the addiction matters when deriving the estimates.

Conducting the first mata-analysis on the alcohol price elasticity that applied the Bayesian model averaging, we managed to employ 23 different aspects of the studies and identify a set of variables that might explain the variation

in the data. However, alcohol price elasticity remains to be an important topic with significant implication to many aspects of the society, therefore an extended view applying new evidence and new data should be considered for the future researches. They should not only consider extending the data on low and medium income countries, but also to many other different aspects that might explain the data variation, like i.e. age, gender, off-premises or on- premises sales, price responsiveness across different income groups, substitution effect with the tobacco and many more. One of the main advantages of the BMA method is that it goes beyond the problem of model selection making strong inference based on all the data available.

Another important aspect that we should not forget is that the price elasticity can have an important implication for the alcohol tax and other price-related policies. If the study demonstrates lower price elasticity as previously suggested, especially for wine and beer, then it indicates that alcohol price policies will likely play a less important role in reducing the alcohol consumption than previously argued. Next important aspect is that heavy drinkers are not responsive to the price changes and any price policy will rather affect the moderate drinkers and not those who contribute to the harmful costs to the society. Therefore, policy makers should rather consider some non-fiscal alcohol policies, like educational anti-drinking campaigns, setting minimum age for alcohol purchase, banning advertising, or limited working hours for the liquor stores and many others.

Bibliography

Aepli, M. (2014): "Consumer demand for alcoholic beverages in switzerland: a two-stage quadratic almost ideal demand system for low, moderate, and heavy drinking households." *Agricultural and Food Economics* **2(1)**.

Anderson, P., D. Chisholm, & D. C. Fuhr (2009): "Effectiveness and cost-effectiveness of policies and programmes to reduce the harm caused by alcohol." *The lancet* **373(9682)**: pp. 2234–2246.

Araya, D. & G. Paraje (2018): "The impact of prices on alcoholic beverage consumption in chile." *PLoS ONE* **13(10)**.

Asplund, M., R. Friberg, & F. Wilander (2007): "Demand and distance: Evidence on cross-border shopping." *Journal of Public Economics* **91(1-2)**: pp. 141–157.

Ayyagari, P., P. Deb, J. Fletcher, W. Gallo, & J. Sindelar (2013): "Understanding heterogeneity in price elasticities in the demand for alcohol for older individuals." *Health Economics (United Kingdom)* **22(1)**: pp. 89–105.

Borenstein, M., L. Hedges, J. Higgins, & H. Rothstein (2009): *Introduction to Meta-Analysis*. A John Wiley and Sons, Ltd., Publicationdż". Cited By 7196.

Borenstein, M., L. V. Hedges, J. P. Higgins, & H. R. Rothstein (2011): *Introduction to meta-analysis*. John Wiley & Sons.

Bray, J., B. Loomis, & M. Engelen (2009): "You save money when you buy in bulk: Does volume-based pricing cause people to buy more beer?" *Health Economics* **18(5)**: pp. 607–618.

Byrnes, J., A. Shakeshaft, D. Petrie, & C. Doran (2016): "Is response to price equal for those with higher alcohol consumption?" *European Journal of Health Economics* **17(1)**: pp. 23–29.

Card, D. & A. B. Krueger (1995): "Time-series minimum-wage studies: a meta-analysis." *The American Economic Review* **85(2)**: pp. 238–243.

Chaloupka, F. J., M. Grossman, & H. Saffer (2002): "The effects of price on alcohol consumption and alcohol-related problems." *Alcohol research & health: the journal of the National Institute on Alcohol Abuse and Alcoholism* **26(1)**: pp. 22–34.

Chelwa, G., P. Toan, N. Hien, L. Thu, P. Anh, & H. Ross (2019): "Do beer and wine respond to price and tax changes in vietnam? evidence from the vietnam household living standards survey." *BMJ Open* **9(5)**.

Cobiac, L., A. Mizdrak, & N. Wilson (2019): "Cost-effectiveness of raising alcohol excise taxes to reduce the injury burden of road traffic crashes." *Injury Prevention* **25(5)**: pp. 421–427.

Dave, D. & H. Saffer (2008): "Alcohol demand and risk preference." *Journal of Economic Psychology* **29(6)**: pp. 810–831.

Duailibi, S., W. Ponicki, J. Grube, I. Pinsky, R. Laranjeira, & M. Raw (2007): "The effect of restricting opening hours on alcohol-related violence." *American journal of public health* **97(12)**: pp. 2276–2280.

Egger, M., G. D. Smith, M. Schneider, & C. Minder (1997): "Bias in meta-analysis detected by a simple, graphical test." *Bmj* **315(7109)**: pp. 629–634.

Eicher, T. S., C. Papageorgiou, & A. E. Raftery (2011): "Default priors and predictive performance in bayesian model averaging, with application to growth determinants." *Journal of Applied Econometrics* **26(1)**: pp. 30–55.

Estruch, R., E. Ros, J. Salas-Salvadó, M.-I. Covas, D. Corella, F. Arós, E. Gómez-Gracia, V. Ruiz-Gutiérrez, M. Fiol, J. Lapetra *et al.* (2013): "Primary prevention of cardiovascular disease with a mediterranean diet." *New England Journal of Medicine* **368(14)**: pp. 1279–1290.

Fanta, N. (2014): *Price Elasticity of Alcohol Demand: A Meta-Analysis.* Master's thesis, Charles University in Prague, Faculty of Social Sciences, Institut of Economic Studies.

Fernandez, C., E. Ley, & M. F. Steel (2001): "Model uncertainty in cross-country growth regressions." *Journal of applied Econometrics* **16(5)**: pp. 563–576.

Fogarty, J. (2006): "The nature of the demand for alcohol: Understanding elasticity." *British Food Journal* **108(4)**: pp. 316–332.

Fogarty, J. (2010): "The demand for beer, wine and spirits: A survey of the literature." *Journal of Economic Surveys* **24(3)**: pp. 428–478.

Fragoso, T. M., W. Bertoli, & F. Louzada (2018): "Bayesian model averaging: A systematic review and conceptual classification." *International Statistical Review* **86(1)**: pp. 1–28.

French, J. (2016): "Economic determinants of wine consumption in thailand." *International Journal of Economics and Business Research* **12(4)**: pp. 334–347.

Furukawa, C. (2019): "Publication bias under aggregation frictions: Theory, evidence, and a new correction method." *Evidence, and a New Correction Method (March 29, 2019)* .

Gallet, C. (2007): "The demand for alcohol: A meta-analysis of elasticities." *Australian Journal of Agricultural and Resource Economics* **51(2)**: pp. 121–135.

Gechert, S., T. Havranek, Z. Irsova, & D. Kolcunova (2020): "Measuring capital-labor substitution: The importance of method choices and publication bias." *An online appendix* pp. 1–49.

Goryakin, Y., B. Roberts, & M. McKee (2015): "Price elasticities of alcohol demand: evidence from russia." *European Journal of Health Economics* **16(2)**: pp. 185–199.

Havranek, T. & Z. Irsova (2017): "Do borders really slash trade? a meta-analysis." *IMF Economic Review* **65(2)**: pp. 365–396.

Janda, K., Z. Lajksnerová, & J. Mikolášek (2019): "A general equilibrium model of optimal alcohol taxation in the czech republic." *Prague Economic Papers* **28(5)**: pp. 589–611.

Janda, K., J. Mikolášek, & M. Netuka (2010): "Complete almost ideal demand system approach to the czech alcohol demand." *Agricultural Economics* **56(9)**: pp. 421–434.

Jiang, H., M. Livingston, R. Room, S. Callinan, M. Marzan, A. Brennan, & C. Doran (2020): "Modelling the effects of alcohol pricing policies on alcohol consumption in subpopulations in australia." *Addiction* .

Kass, R. E. & A. E. Raftery (1995): "Bayes factors." *Journal of the american statistical association* **90(430)**: pp. 773–795.

Keyes, K., A. Shev, M. Tracy, & M. CerdĂˇ (2019): "Assessing the impact of alcohol taxation on rates of violent victimization in a large urban area: an agent-based modeling approach." *Addiction* **114(2)**: pp. 236–247.

Kumar, S. (2017): "Price elasticity of alcohol demand in india." *Alcohol and Alcoholism* **52(3)**: pp. 390–395.

Laković, T., A. Mugoša, M. Čizmović, & G. Radojević (2019): "Impact of taxation policy on household spirit consumption and public-finance sustainability." *Sustainability* **11(20)**: p. 5858.

Leon, D. A., L. Saburova, S. Tomkins, E. Andreev, N. Kiryanov, M. McKee, & V. M. Shkolnikov (2007): "Hazardous alcohol drinking and premature mortality in russia: a population based case-control study." *The Lancet* **369(9578)**: pp. 2001–2009.

Mäkelä, P. & E. Österberg (2009): "Weakening of one more alcohol control pillar: a review of the effects of the alcohol tax cuts in finland in 2004." *Addiction* **104(4)**: pp. 554–563.

Meier, P. S., R. Purshouse, & A. Brennan (2010): "Policy options for alcohol price regulation: the importance of modelling population heterogeneity." *Addiction* **105(3)**: pp. 383–393.

Meng, Y., A. Brennan, R. Purshouse, D. Hill-McManus, C. Angus, J. Holmes, & P. Meier (2014): "Estimation of own and cross price elasticities of alcohol demand in the uk-a pseudo-panel approach using the living

costs and food survey 2001-2009." *Journal of Health Economics* **34(1)**: pp. 96–103.

Naimi, T. S., Z. Xuan, S. E. Cooper, S. M. Coleman, S. E. Hadland, M. H. Swahn, & T. C. Heeren (2016): "Alcohol involvement in homicide victimization in the united states." *Alcoholism: clinical and experimental research* **40(12)**: pp. 2614–2621.

Nelson, J. (2013): "Meta-analysis of alcohol price and income elasticities - with corrections for publication bias." *Health Economics Review* **3(1)**: pp. 1–10.

Nelson, J. (2014): "Estimating the price elasticity of beer: Meta-analysis of data with heterogeneity, dependence, and publication bias." *Journal of Health Economics* **33(1)**: pp. 180–187.

Pierani, P. & S. Tiezzi (2009): "Addiction and interaction between alcohol and tobacco consumption." *Empirical Economics* **37(1)**: pp. 1–23.

Prest, A. R. (1949): "Some experiments in demand analysis." *The Review of Economics and Statistics* pp. 33–49.

Pryce, R., B. Hollingsworth, & I. Walker (2019): "Alcohol quantity and quality price elasticities: quantile regression estimates." *European Journal of Health Economics* **20(3)**: pp. 439–454.

Rabinovich, L., P.-B. Brutscher, H. de Vries, J. Tiessen, J. Clift, & A. Reding (2009): "The affordability of alcoholic beverages in the european union." *European Commission, RAND Corporation, UK* .

Raftery, A. E., D. Madigan, & J. A. Hoeting (1997): "Bayesian model averaging for linear regression models." *Journal of the American Statistical Association* **92(437)**: pp. 179–191.

Ramful, P. & X. Zhao (2008): "Individual heterogeneity in alcohol consumption: The case of beer, wine and spirits in australia." *Economic Record* **84(265)**: pp. 207–222.

Rehm, J., B. Taylor, & J. Patra (2006): "Volume of alcohol consumption, patterns of drinking and burden of disease in the european region 2002." *Addiction* **101(8)**: pp. 1086–1095.

Rosenthal, R. (1979): "The file drawer problem and tolerance for null results." *Psychological bulletin* **86(3)**: p. 638.

Ruhm, C., A. Jones, K. McGeary, W. Kerr, J. Terza, T. Greenfield, & R. Pandian (2012): "What u.s. data should be used to measure the price elasticity of demand for alcohol?" *Journal of Health Economics* **31(6)**: pp. 851–862.

Schwartz, L. M., E. C. Persson, S. J. Weinstein, B. I. Graubard, N. D. Freedman, S. Männistö, D. Albanes, & K. A. McGlynn (2013): "Alcohol consumption, one-carbon metabolites, liver cancer and liver disease mortality." *PloS one* **8(10)**.

Scottish-Government (2018): *Alcohol Framework 2018:Preventing Harm.* Scottish Government.

Selvanathan, S. & E. A. Selvanathan (2007): "Another look at the identical tastes hypothesis on the analysis of cross-country alcohol data." *Empirical Economics* **32(1)**: pp. 185–215.

Sharma, A., K. Sinha, & B. Vandenberg (2017): "Pricing as a means of controlling alcohol consumption." *British Medical Bulletin* **123(1)**: pp. 149–158.

Sornpaisarn, B., K. Shield, J. Cohen, R. Schwartz, & J. Rehm (2013): "Elasticity of alcohol consumption, alcohol-related harms, and drinking initiation in low- and middle-income countries: A systematic review and meta-analysis." *The International Journal of Alcohol and Drug Research* **2(1)**.

Spach, M. (2017): *Tobacco and Alcoholic Beverage Consumption of European Adolescents: Substitutes or Complements? The Value of an All-encompassing Policy.*

Srivastava, P., K. Mclaren, M. Wohlgenant, & X. Zhao (2015): "Disaggregated econometric estimation of consumer demand response by alcoholic beverage types." *Australian Journal of Agricultural and Resource Economics* **59(3)**: pp. 412–432.

Stanley, T. D. (2005): "Beyond publication bias." *Journal of economic surveys* **19(3)**: pp. 309–345.

Stanley, T. D. & H. Doucouliagos (2012): *Meta-regression analysis in economics and business*, volume 5. Routledge.

Stanley, T. D., S. B. Jarrell, & H. Doucouliagos (2010): "Could it be better to discard 90% of the data? a statistical paradox." *The American Statistician* **64(1)**: pp. 70–77.

Steel, M. F. & E. Ley (2007): *On the effect of prior assumptions in Bayesian model averaging with applications to growth regression*. The World Bank.

Stevens, J. & J. Childs (2017): "Re-examining the economic determinants of alcohol consumption in canada: controlling for the presence of common correlated effects." *Applied Economics Letters* **24(16)**: pp. 1177–1180.

Stockwell, T., M. C. Auld, J. Zhao, & G. Martin (2012): "Does minimum pricing reduce alcohol consumption? the experience of a canadian province." *Addiction* **107(5)**: pp. 912–920.

Thornton, A. & P. Lee (2000): "Publication bias in meta-analysis: its causes and consequences." *Journal of clinical epidemiology* **53(2)**: pp. 207–216.

Tomlinson, P. & J. Branston (2014): "The demand for uk beer: Estimates of the long-run on- and off-trade beer price elasticities." *Applied Economics Letters* **21(3)**: pp. 209–214.

Vitaliano, D. (2015): "Repeal of prohibition: A benefit-cost analysis." *Contemporary Economic Policy* **33(1)**: pp. 44–55.

Wagenaar, A. (2010): "Alcohol price policies: Connecting science to practice." *Addiction* **105(3)**: pp. 398–399.

Wagenaar, A., M. Salois, & K. Komro (2009): "Effects of beverage alcohol price and tax levels on drinking: A meta-analysis of 1003 estimates from 112 studies." *Addiction* **104(2)**: pp. 179–190.

WHO (2019): *Global status report on alcohol and health 2018*. World Health Organization.

Xu, X. & F. Chaloupka (2011): "The effects of prices on alcohol use and its consequences." *Alcohol Research and Health* **34(2)**: pp. 236–245.

Xuan, Z., F. Chaloupka, J. Blanchette, T. Nguyen, T. Heeren, T. Nelson, & T. Naimi (2015): "The relationship between alcohol taxes and binge drinking: Evaluating new tax measures incorporating multiple tax and beverage types." *Addiction* **110(3)**: pp. 441–450.

Yeh, C.-Y., L.-M. Ho, J.-M. Lee, & J.-Y. Hwang (2013): "The possible impact of an alcohol welfare surcharge on consumption of alcoholic beverages in taiwan." *BMC Public Health* **13(1)**.

Zeugner, S., M. Feldkircher *et al.* (2015): "Bayesian model averaging employing fixed and flexible priors: The bms package for r." *Journal of Statistical Software* **68(4)**: pp. 1–37.

Appendix A

Data overview

Below table A.1, shows how the data are dispersed per country. Table A.2, groups the data per region. Under the same criteria we explore the cross-country variation in Chapter 6.

- Anglosphere - data refers to Australia, Canada, New Zealand, UK and USA;
- Russia - if the data refers to Russia. Since the data were highly correlated to the variable daily, we removed Russia from the estimation;
- Northern Europe - if the date refers to Denmark, Finland, Norway and Sweden;
- Western Europe - if the data refers to France, Switzerland, Germany, Austria, Belgium, The Netherlands, Czechia;
- Southern Europe - if the the estimate is for Cyprus, Greece, Portugal, Italy;
- Japan - if the estimate is for Japan;
- LMIC - if the data refers to Chile, India, Montenegro, Taiwan, Thailand, Vietnam;

Table A.1: Data dispersion per country

Country	Data/percent
Australia	8.31
Canada	12.85
Chile	0.76
China	1.51
Cyprus	1.26
Czechia	0.76
Denmark	1.76
Finland	2.27
France	1.01
India	0.50
Japan	1.51
Montenegro	1.51
New Zealand	3.02
Northern Europe	0.50
Norway	2.27
Russia	12.09
Southern Europe	0.50
Sweden	5.29
Switzerland	3.02
Taiwan	1.01
Thailand	0.50
UK	16.37
USA	18.89
Vietnam	2.02
Western Europe	0.50

Table A.2: Data dispersion per group of countries

Country	Data/percent
Anglosacsonic	59.44
Russia	12.09
Northern Europe	12.09
Western Europe	5.29
Southern Europe	1.76
Japan	1.51
LMIC	7.81

Figure A.1: Identification of influential studies

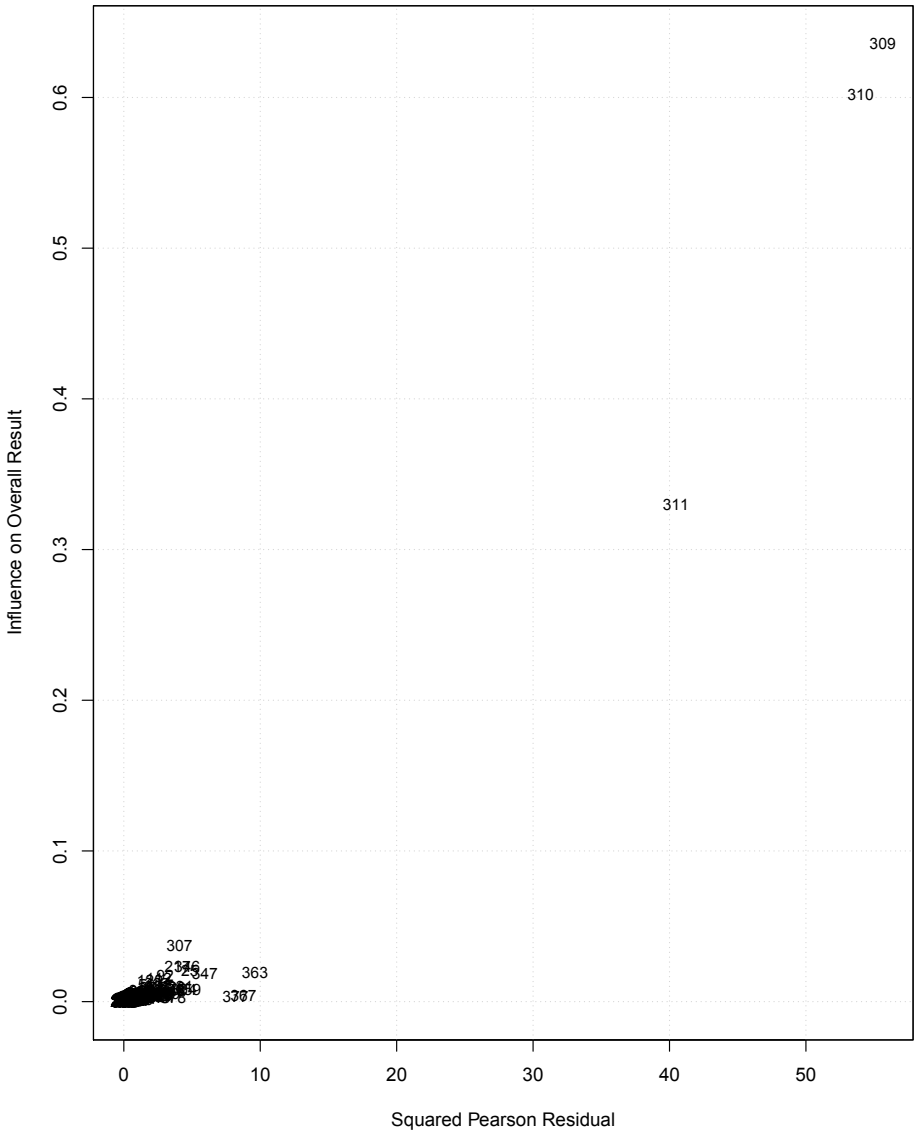


Figure A.2: Alcohol elasticity estimates

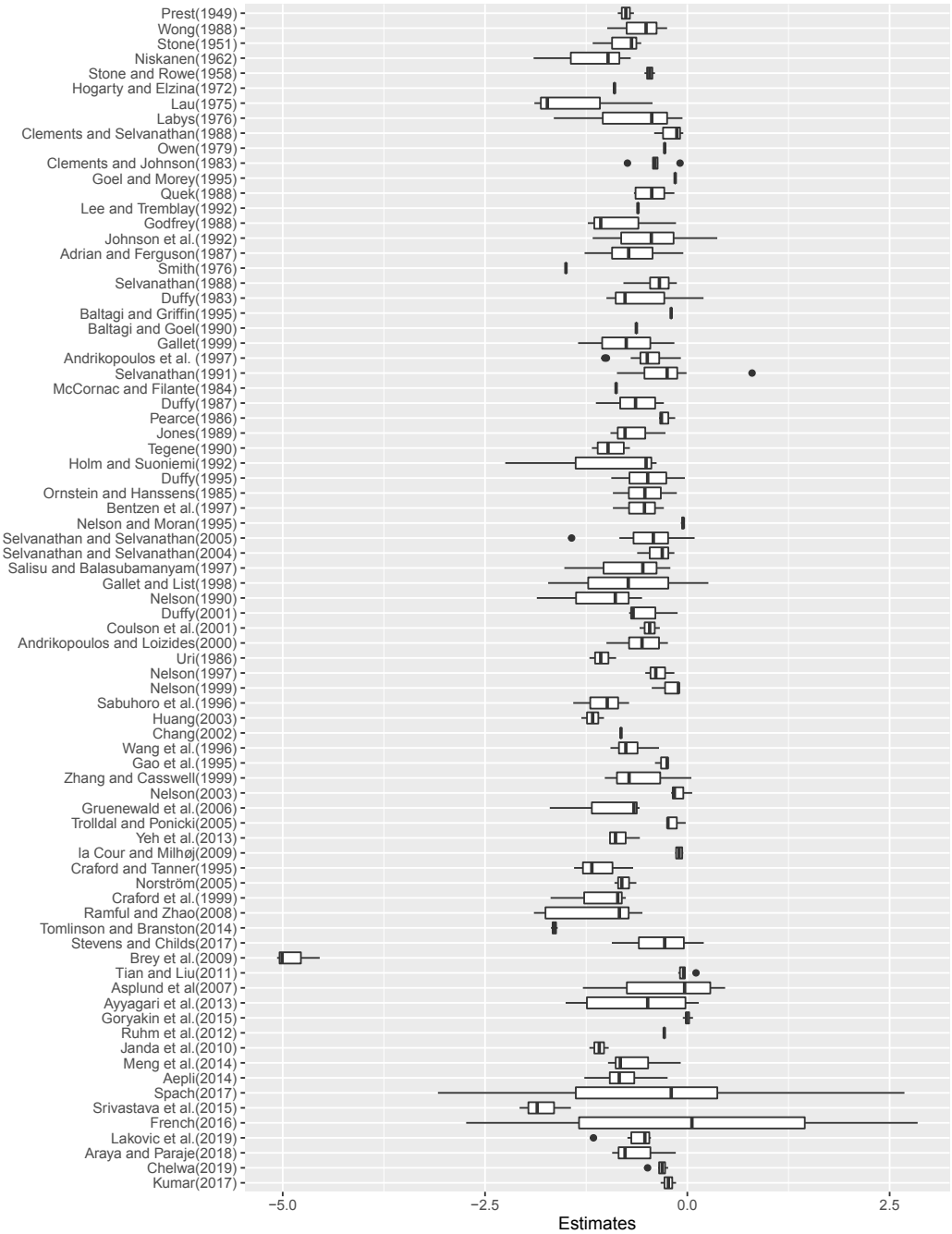


Figure A.3: Beer elasticity estimates

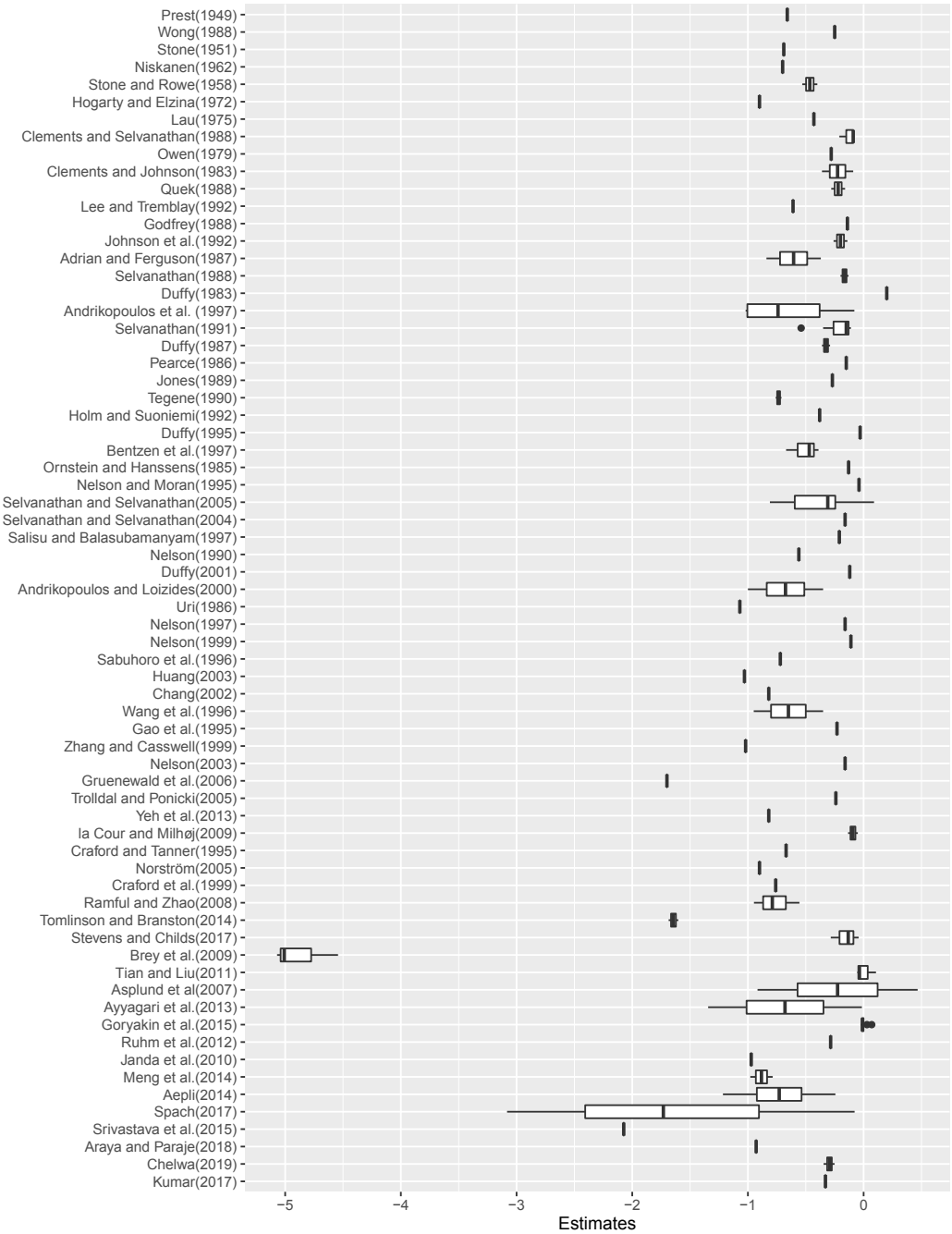
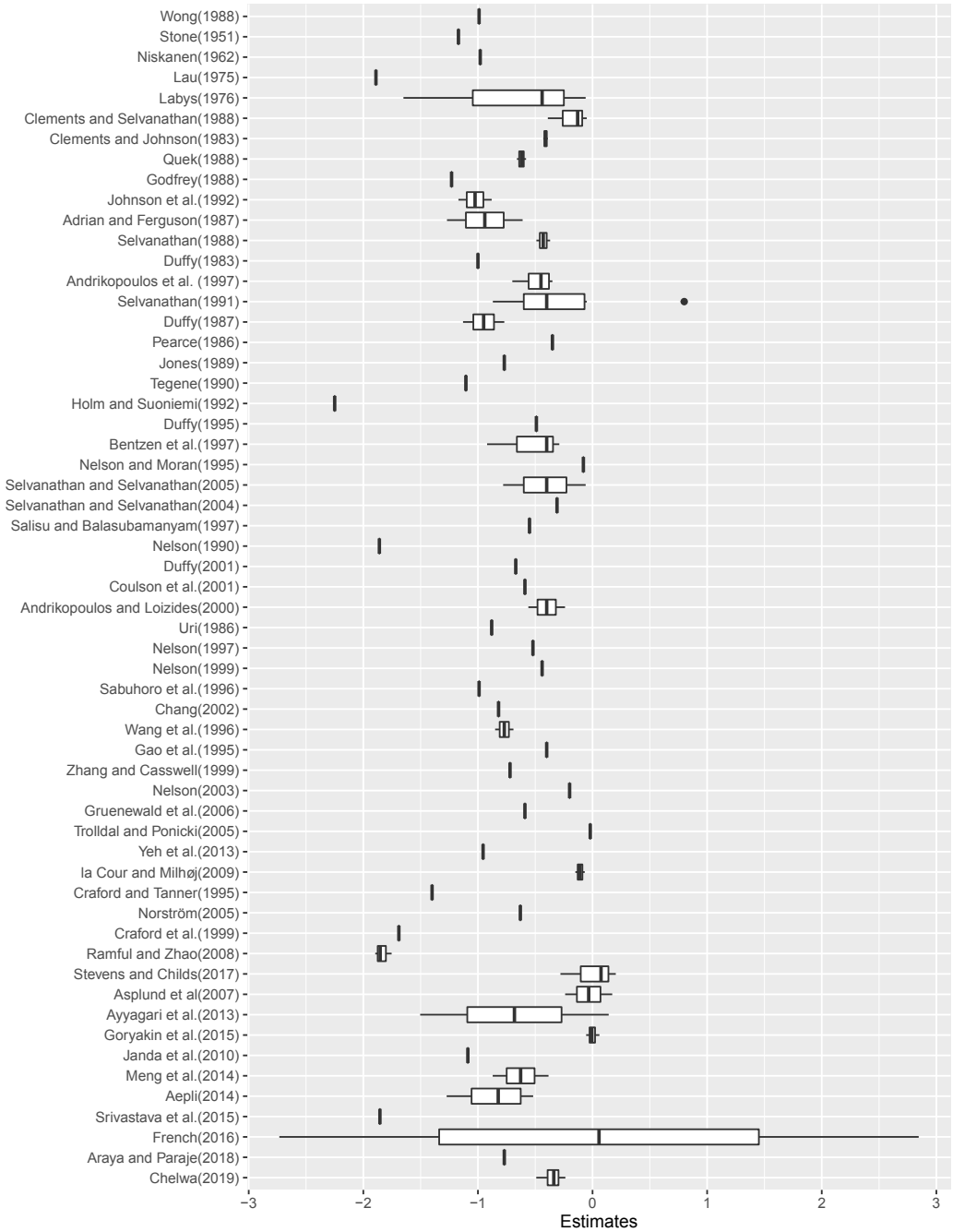


Figure A.4: Wine elasticity estimates



Appendix B

A "Stem-based" bias correction method

To compute the estimates corrected for the bias the author applied two algorithms (Furukawa 2019).
The inner algorithm estimates the true effect $\hat{b}_{stem}$, its standard error $SE(\hat{b}_{stem})$ and the optimal number of precise studies n_{stem}, with an assumed value of the variance σ_0.
First, the studies will be ranked and indexed in an ascending order to the standard error, SE, and then for each $n = 2, \ldots, N$, a relevant $\tilde{Bias}^2(n)$ and the variance will be computed, given the weights $\omega_i = \frac{1}{\sigma_i^2+\sigma_0^2}$,

$$\tilde{Bias}^2(n) = \frac{\sum_{i=2}^{n}\sum_{j\neq i}^{n}\omega_i\omega_j\beta_i\beta_j}{\sum_{i=2}^{n}\sum_{j\neq i}^{n}\omega_i\omega_j} - 2\beta_1\frac{\sum_{i=2}^{n}\omega_i\beta_i}{\sum_{i=2}^{n}\omega_i} \tag{B.1}$$

$$Var(n) = \sum_{i=1}^{n}\omega_i \tag{B.2}$$

Then the optimal number of included studies,n_{stem} is computed by minimizing the mean squared error by solving as previously given in the equation 5.1, or as follows:

$$\min_n MSE(n) = Bias^2(n) + Var(n) \tag{B.3}$$

Hence, the stem-based estimate $\hat{b}_{stem}$ and its standard error $SE(\hat{b}_{stem})$ would be:

$$\hat{b}_{stem} = \frac{\sum_{i=1}^{n_{stem}}\omega_i\beta_i}{\sum_{i=1}^{n_{stem}}\omega_i} \tag{B.4}$$

$$SE(\hat{b}_{stem}) = \frac{1}{\sqrt{\sum_{i=1}^{n_{stem}} \omega_i}} \tag{B.5}$$

By applying the inverse of the variance weights, the $\hat{b}_{stem}$ minimizes the variance of the estimator. Then the outer algorithm searches for σ_0^2, such that the implied variance will be consistent with the assumed one.

Appendix C

Bayesian model averaging

Figure C.1: Model size and convergence

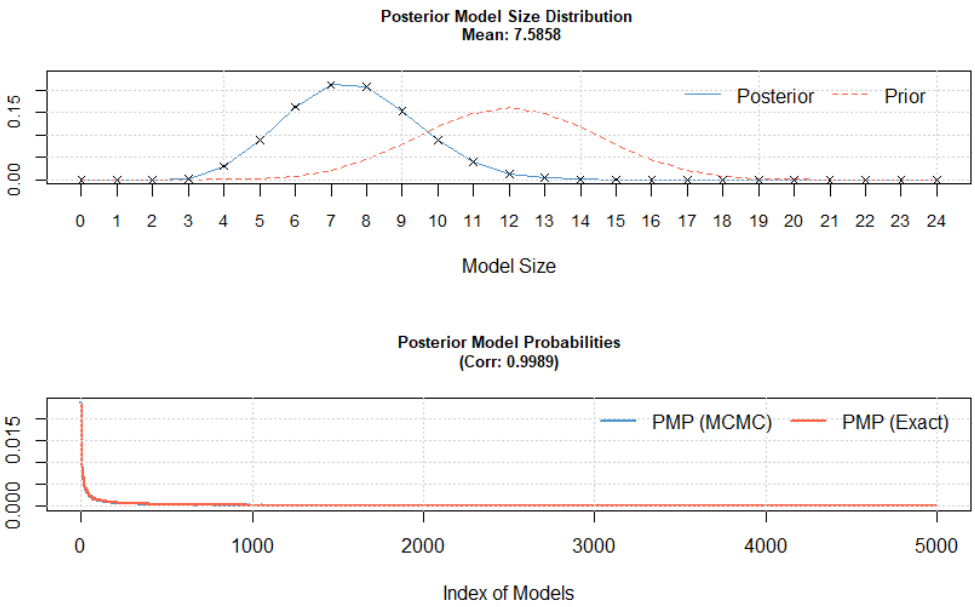


Table C.1: Alternative "best" model

Response variable:	Bayesian model averaging			Frequentist check (OLS)		
Estimate of elasticity	Post.mean	Post.SD	PIP	Coef.	Std.er.	p-value
SE(publication bias)	-0.512	0.098	1.000	-0.542	0.232	0.022
Type of beverages						
Wine	-0.054	0.071	0.444			
Spirits	-0.021	0.049	0.199			
Estimation approaches						
Time-series	0.004	0.025	0.051			
Cross-sectional	0.007	0.038	0.059			
Panel	0.002	0.019	0.044			
System-wide	-0.001	0.012	0.039			
Countries data						
Northern Europe	0.001	0.013	0.032			
Western Europe	0.004	0.028	0.044			
Southern Europe	0.005	0.043	0.040			
Japan	0.124	0.204	0.328			
LMIC	0.113	0.133	0.494			
Frequency						
Quarterly	0.003	0.022	0.046			
Monthly	-0.024	0.072	0.143			
Daily	0.389	0.076	1.000	0.370	0.076	0.000
Demand specification						
Unconditional	-0.129	0.071	0.849	-0.147	0.066	0.030
Hicksian	-0.001	0.012	0.035			
Data characteristics						
Number of Years	0.140	0.029	1.000	0.125	0.036	0.001
Import	-0.051	0.102	0.252			
Long Run	-0.023	0.062	0.158			
Addiction	-0.003	0.021	0.051			
Publication						
Publication year	0.001	0.002	0.185			
Citations	0.005	0.011	0.248			
Journal impact	0.004	0.005	0.457			
Constant	-0.857		1.000	-0.744	0.143	0.000
Observations	391			391		

Notes: SD = standard deviation, PIP = posterior inclusion probability, LMIC = low and medium income countries. In the frequentest check we include only explanatory variables with PIP > 0.8. The standard error in the frequentest check (OLS) are clustered at the study level. All the variables are described in details in Table 6.1