Charles University in Prague

Faculty of Social Sciences

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BACHELOR THESIS

Price Elasticity of Alcohol Demand: A Meta-Analysis

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Academic Year: **2013/2014**

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Prague, July 24, 2014

Signature

Acknowledgments

The author is grateful especially to his coordinator PhDr. Tomáš Havránek Ph.D. for his advice and help. Many thanks are also addressed to James Fogarty BEc Ph.D. who agrreed with the use of his dataset for the meta-analysis. The author is also grateful to his family members and his grand-father for their support and motivation.

Abstract

The own-price elasticity is considered to be one of the key factors describing the demand for alcohol. There have been many estimates computed by now but only a few studies tried to analyze them. The aim of this meta-analysis is to discover more about the eventual effects that publication bias might have in the alcohol-related literature. The first part describes the various types of elasticities and the methods of estimation. This study is estimating the so called true effect elasticity in order to show how elastic the demand for alcoholic beverages is. As there are many ways how to estimate the elasticities it is also analyzed if different approaches to the estimation lead to different results. The use of modern meta-analytical methods leads to significantly different results from the ones of previous meta-analyses. The estimated true effects yields new evidence that the demand for alcoholic beverages might be perfectly inelastic. Evidence of publication bias is quite strong and it appears that the economics research cycle hypothesis is also valid.

JEL Classification	C81, D12, Q11
Keywords	alcohol, meta-analysis, price, elasticity, demand

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Abstrakt

Vlastní cenová elasticita je považována za jeden z klíčových faktorů k vysvětlení poptávky po alkoholu. Odhadů bylo vypočítáno už mnoho, ale analyzovalo je jen několik prací. Cílem této meta-analýzy je prozkoumat možné vlivy publikační selektivity v literatuře věnující se alkoholu. Úvodní část popisuje jednotlivé druhy elasticit a způsoby výpočtu. V této práci je odhadována takzvaná původní elasticita, aby se ukázalo, jak je vlastně poptávka po alkoholu elastická. Jelikož existuje mnoho způsobů odhadování elasticit, je také zkoumáno, jestli rozdílné přístupy k odhadování vedou i k odlišným výsledkům. Použití nejnovějších meta-analytických nástrojů vede k výrazně odlišným výsledkům, než přináší předchozí meta-analýzy. Odhadovaná původní elasticita přináší nové důkazy o tom, že poptávka po alkoholických nápojích by mohla být dokonale neelastická. Objevují se dále důkazy potvrzující výskyt publikační selektivity a ukazuje se také, že platí i hypotéza ekonomického cyklu.

Klasifikace JEL	C81, D12, Q11
Klíčová slova	alkohol, metaanalýza, cena, elasticita, poptávka

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Acronyms

FAT Funnel Asymmetry Test

OLS Ordinary Least Squares

PET Precision-effect Test

Bachelor Thesis Proposal

Author	Nicolas Fanta
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Proposed topic	Price Elasticity of Alcohol Demand: A Meta-Analysis

Topic characteristics The estimation of the price-elasticity of demand for alcohol has been evolving rapidly since the last thirty years. Such evolution was caused by the increased attention to the demand for alcoholic beverages and its negative externalities. Only a few meta-analyses studies these estimates but the issue of publication bias affecting the literature was not examined that much.

Hypotheses The assumption that the true effect elasticity is supposed to be negative might be one of the causes of the presence of publication bias. Therefore the true effect is going to be estimated and tests to detect publication bias will be done. The presence of publication bias is expected as the demand for alcohol is not likely to be elastic. It is also expected to that there are some methods that lead to higher magnitudes of the result and thus overestimate the elasticity in comparison to others.

Methodology Graphical tools such as the Funnel and Galbraith plots will be used in order to detect evidence indicating the presence of publication bias. The true effect will be estimated by an equation for the FAT and PET tests. The mixed effects estimation will be used in order to estimate the model. The analysis of heterogeneity in the estimation approaches will use the multilevel mixed-effects approach.

Outline

1. Introduction

2. Methods of estimation
3. The new dataset
4. The combined dataset
5. Meta regression - Heterogeneity analysis
6. Conclusion

In the first part of the thesis it is going to be explained what are the various methods employed to the estimation, what are their pros and cons. The second part of the study is based on the analysis of the data. There are two datasets: one consists of newly collected data (the new dataset), the other is the updated dataset (the combined dataset) used in the meta-analysis of Fogarty (2010). Both of these datasets will be analysed separately. The last part of the thesis is going to see if the heterogeneity in the estimation approaches affects the results.

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Author Supervisor

Chapter 1

Introduction

Since the 1980s there have been many studies trying to find the link between the prices of alcoholic beverages and some eventual negative externalities such as alcohol-related mortality, car accidents or crime levels in order to clarify the causality. As it was often discovered that a rise in prices reduces the consumption and the negative impacts, the taxation of alcohol became of key interest to governments. The increase in taxes does not represent the only tool to reduce the consumption of alcohol and its negative consequences. Raising awareness of the health complications related to an excessive consumption is mandatory in some countries usually in form of labels discouraging from drinking before driving of when being pregnant.

Advertising and marketing alcohol is often regulated or even banned. The introduction of severe penalties for driving under the influence of alcohol is supposed to decrease the number of car accidents. Some countries also use licensing as way how to reduce the number of places where alcohol can be acquired (the USA for example). In the Scandinavian countries, for instance, the regulation went even further - the governments forbid to sell alcohol in common supermarkets, it can be sold only in state-owned monopolies (e.g. Systembolaget in Sweden). Such monopoly combines several methods of regulation: the number of shops selling alcohol is significantly reduced so the time costs to get alcohol increase, the opening hours reduce the availability of alcohol during the weekends, the pricing of various products is fully supervised, and finally the government can also control the location where alcohol can be sold (Chaloupka *et al.* 2002).

Chaloupka *et al.* (2002) consider the excise tax the most efficient tool to reduce alcohol consumption. Unfortunately this tool is often not used at its

full power. For example in 1951 16 cents per six-pack of beer were charged for tax in the US. The tax was raised again in 1991 to 32 cents per six pack but, because of inflation, it failed to reach the same level as in 1951. Chaloupka *et al.* (2002) calculated that to have the same effect the tax should have been set up to 84 cents. It is therefore questionable whether such a change was done in order to reduce consumption or simply raise some more funds for the government.

1.1 Reasons why elasticities are computed

The knowledge of price-elasticity appears to be helpful when studying the relationship between the price and the consumption of various alcoholic beverages. Such information is very handy in various areas. The most obvious could be the maximisation of government revenues from alcohol taxes. The elasticity estimates represents one of the key inputs to determine the optimal taxation. In some countries the costs of the negative externalities of an excessive alcohol consumption can be very high. Many studies tried to analyse the link between the price of alcohol and some negative outcomes due to its abuse. For instance Chaloupka & Wechsler (1996) analysed how a potential policy which would introduce the same tax as in 1951 (compensated for inflation) would affect the number of car accidents of US students. Interestingly the effect (obviously negative) was significant only for female students.

A good understanding of the alcohol demand can be beneficial for the healthcare policymakers as well. Ohsfeldt & Morrisey (1997) studied the link between non-fatal workplace injuries and beer taxes. The researchers found out that a 25 cent increase in the beer tax in the US would reduce the cost of loss in productivity caused by such injuries by $491 million. Other studies examined if the number deaths related to alcohol consumption can be reduced by increasing its price. In contrast to previous studies Sloan *et al.* (1994), who studied mostly deaths from liver cirrhosis and the change in prices of alcohol, did not find a significant effect.

Another reason why elasticity estimates are computed is because of the information about consumer preferences they yield. Bray *et al.* (2009) tried to discover about the beer consumer behaviour. To be more specific he computed elasticities for 3 types of beer packages (6, 12 and 24-packs) in the US. For instance a 10% ceteris paribus decrease in the price of 6-packs would increase the sales of six packs by 50,71%, 12-packs by -11,73% and 24-packs by -12,32%.

Similarly a 10% decrease in the price of 12-pacs would decrease the sales of 6-packs by 19,02%, increase the sales of 12-packs by 50,08% and decrease the sales of 12-packs by 2,44%. Therefore it can be noticed that a decrease in the price of 6-packs would interestingly decrease the total volume of beer sold as the increase in the sales of 6-packs would not compensate for the loss in the sales of 12-packs. Contralily to that a 10 % decrease in the price of 12-packs or 24-packs would increase total beer sales. Such knowledge may help to improve pricing strategies of the producers or retailers.

There have also been studies investigating the impact of an increase in the prices of alcohol on violence and crime. There was even a study (Cook & Moore 1993) using US data that discovered that an increase in the price of beer would have a significant decrease in robberies and rapes but the impact would not be that important for homicides and assaults.

To sum it up there are several reasons for computing price elasticities. A question now arises: are the researchers motivated to report statistically significant results? It seems that they are, because the ones who hired them are looking for reliable numbers for their new policies or marketing strategies If statistically significant results were preferred what would that mean? Without preferences for any kind of results the distribution of the estimates is supposed to be normally (and symmetrically) distributed around some mean value. As alcohol is expected to be a normal good negative estimates are highly expected. Their significance can be either achieved by increasing the magnitude of the effect or by reducing its standard error. Such actions can lead to a skewed distribution of the estimates and an unusual number of high precision estimates. Another problem that arises with the purposely amplified magnitudes of some of the estimates in the sample is that the average of the sample is no longer an unbiased estimator of the true effect. This bachelor thesis is going to reveal evidence about such bias and corrected estimates of the true effects will be computed.

Chapter 2

Methods of estimation

There are many factors influencing the estimation of alcohol elasticities: data type (aggregated or individual), source (national or cross-sectional), price or tax rate, age groups, measure of consumption (sales, quantity or frequency). Also the elasticity interpretation itself varies across the publications. In many cases there are separate estimates for each kind of beverage category: beer, spirits and wine whereas in other papers the categories are even more specified. For instance in Bray *et al.* (2009) there is an estimate for each kind of beer-package in order to analyse the demand for different brands and packages of beer. On the other hand there are studies such as Murphy *et al.* (2009) where there is a single elasticity estimates for all alcoholic beverages. This is often the case of health care studies that monitor different kind of addiction to drugs where for the simplicity of comparison it is better to have only one elasticity estimate for each kind of addictive drug. The meta-analyst has to regroup such different kinds of estimates in order to identify the heterogeneity in them and regroup those according to common characteristics. One would think that the price elasticity of beer is a clear term but after analysing a few studies related to the topic it is clear that more specification is needed because of the variety of methodologies. Sometimes the differences in those are negligible, sometimes explanations are missing therefore coding the dataset is often considered the longest and most complicated part of the study.

2.1 The demand

In the empirical studies the terms of Conditional and Unconditional demands can be encountered. Selvanathan & Selvanathan* (2004) describe the uncon-

ditional demand equation as "*the consumer's demand equation derived from a general utility function for all n goods in terms of all n prices and total expenditure*" and the conditional demand equation as an equation that "*depends only on variables pertaining to the alcoholic beverages group*" (Selvanathan & Selvanathan 2007). The interpretation of the price elasticities therefore depends on the demand's type. Consider a price change of beverage i holding other prices and real income constant. The conditional demand equation of beverage i describes how the consumption will adapt after a change in the price of beverage i holding the expenditure on (in our case) alcoholic beverages and other beverages' prices constant. The unconditional estimates are more responsive to a price change (Fogarty 2010) because they are not restricted to a specific group of goods. More goods means more eventual substitutes therefore a higher propensity to change the consumption behaviour in the case of a ceteris paribus change in the price of one of the goods.

In microeconomics two different types of demand equations can be identified. The most common ones are the compensated (Hicksian) and uncompensated (Marshallian) demands. Let us consider a change in the price of product i while holding other prices and the (nominal) wealth constant, the uncompensated demand for i indicates how such a change in the price of i will affect the demand for i. The compensated demand indicates how a price change of product i, holding other prices and the real wealth constant, will affect the demand for i. It is called compensated because the real wealth has to be compensated so that the consumer's real wealth remains constant. In other words he must maintain the same utility as he had before the price change. According to Fogarty (2010) academic economists are more interested in the pure price effect (as they want to study the utility function) so they usually tend to report Hicksian price-elasticity estimates. On the other hand policy makers are interest more in the real uncompensated effect (as they are interested in total change in consumption) therefore they are more interested in the Marshallian estimates.

Alcohol can be considered as a normal good (for the majority of the population) due to the fact that it has very few substitutes most of which are illegal. Consider now the Slutsky equation. Knowing that alcohol is a normal good, it can be easily derived from the Slutsky equation that it is also a common good. As the Hicksian own-price elasticity is always non-positive and from the information that alcohol is a normal and a common good Marshallian own-price elasticity estimates of alcohol are expected to be more elastic than the Hicksian

ones (the proof can be found in the Appendix A). If the beverage categories are taken into consideration, the assumption that all of the beverage categories are normal goods might not hold as in some countries there can be a beverage category considered as an inferior good. For instance cheap wine can be an inferior good and a substitute for beer.

The approaches to demand estimation varied across time. The first approach to estimate the price-elasticity of alcohol was the utility free approach which consisted often in using a single equation estimation model. A good example of this approach can be found in the studies of Stone (1945) or Prest (1949). Since then the approaches have evolved into much more complex ones, called system-wide utility based estimation approaches. The most commonly used models that are being used nowadays are the Rotterdam and the Almost Ideal Demand System (AIDS) models. The study of Janda *et al.* (2010) gives a good example of the AIDS model.

2.1.1 Aggregated alcohol consumption versus specific beverage consumption

A common trend in many studies is to aggregate the alcohol consumption over sub-categories (e.g. beer, wine and spirits) by units of 100% alcohol equivalents. Goryakin *et al.* (2014) in his study criticises this approach for two reasons: people may be less accurate when reporting their consumption (e.g. social acceptability reasons) and also such an approach requires to make assumptions about the alcohol content in different beverages. Another problem of this approach is that the price of alcohol often varies depending on the sub-category (wine might be cheaper than spirits in term of price per alcohol unit). The causes can be different taxation or simply different production costs. Therefore such elasticity estimates need not be very informative to policy-makers as they cannot directly interpret the demand for each of beverage categories. This approach is often used to monitor the behaviour of different types of drug addictions in medical paper as it brings a clearer information about the pure alcohol quantity consumed and makes it comparable with the consumption of other drugs. For the purpose of this meta-analysis aggregated alcohol consumption estimates will not be examined as the alcoholic beverages can be divided into 3 different categories.

The other approach to the demand estimation is to define a few subcategories of alcohol beverages. The benefit of such an approach is that the

estimates can be used further as an important input for taxation policy. In some studies elasticity estimates can be even more specific so that they can describe the consumer's preferences (e.g. for various types of beer packages Bray *et al.* (2009)). At first glance it may appear that the price-elasticity for alcohol beverages (beer, wine and spirits) should be close to zero but within those categories alcohol consumers tend to have a much more elastic demand (as there are many brands and other sub-category characteristics: red, white or rosé wines for instance).

2.2 How prices are measured

A measure of price is always necessary when estimating the own-price elasticity. Two different ways can be found in the literature: the first is taking the usual retail price and the other is the usage of taxes as an approximation. The rationale of the usage of taxes according Kenkel (2005) is that "*in a perfectly competitive environment, where the marginal costs of production are constant, the taxes will be fully passed to consumers*". It means that a 1 cent increase in tax will lead to a 1 cent increase in price. It is questionable to which extent the taxes pass to prices as the demand and competition differ a lot depending on the market. For instance intense competition can cause that an increase in tax may not affect the retail price (and thus reduce the profit margin of the retailer). On the other hand no one will dispute the fact that taxes and prices of alcohol are highly correlated. The benefit of using taxes as an approximation to prices is simplicity as there is no need to aggregate and collect numerous retail prices. Ruhm *et al.* (2012) in his study criticises such approach for several reasons: there are countries (e.g.the USA) where taxes form only a very small part of the prices so they almost do not affect them, as excise taxes do not change very often most of the changes in real rates are due to inflation, finally taxes can be endogenously determined. A spurious negative correlation between taxes and use can arise in countries with strong anti-drinking policies and high taxes. The use of the tax as an approximation of prices is therefore questionable. On the other hand collecting retail prices might be much more difficult and costly in terms of time. Thus taxes can be used for smaller studies that should be done relatively fast but larger studies should not use the tax approximation.

2.3 Data type

Two kinds of data are used in the studies: aggregate and individual. The aggregate data report the total amount of alcohol consumed in a certain region by a large group of people. Individual data on the other hand report the amount of alcohol consumed by specific persons. According to Chaloupka *et al.* (2002) aggregate data might face a problem when estimating the price levels. For instance when monitoring the consumption behaviour of students in the US, the average of the retail prices of alcohol might not be a good proxy for the price the students pay as most of the parties are held in places where alcohol is on sale to attract them or is sold with no charge. Meng *et al.* (2014) see also a weakness in the fact that national aggregate time-series data do not have so many observations. The cross-sectional data according to Meng *et al.* (2014) tend to have endogeneity problems. The cross-section often do not monitor time-invariant variables that differ a lot between individuals (and are correlated to the prices) such as personal or quality tastes. This results in the fact that the variation caused by these tastes is then wrongly attributed to the price. The drawbacks of having individual data consist mostly in the costs of getting them. The sample size is usually smaller, the time-series is shorter and often tend to suffer more from non-response.

A solution to the issues of the aggregate and individual data is presented by Holmes *et al.* (2014), who uses a pseudo-panel for his estimation. Instead of analysing individuals, it analyses subgroups of the population. The assumption for these subgroups relies in the fact that people might go from one group to another but the group itself keeps the same characteristics over time (endogeneity can be avoided because it is easier to include personal tastes into the model). It is then up to the researcher to choose between having a large number of subgroups with a small within-group heterogeneity or having large groups with a larger within-group heterogeneity.

2.4 Previous meta-analyses

As alcohol is broadly discussed and the numbers of elasticity estimates skyrocketed in the past years there have been several meta-analyses related to this topic. The first two, Gallet (2007) and Fogarty (2004), are based on simple OLS estimation methods. The meta-analyses are studying both price and income-elasticity estimates of beer, wine, and spirits. Several objections can be made

to these studies. Both do not correct for heteroscedasticity which is obviously present in the literature as it will be discussed later. Precision of each estimate is not taken into account therefore estimates reported by large studies have the same weight as the ones from small studies. It is also not clear how the authors dealt with outliers and finally publication bias is not examined at all. As some of the authors often wrote more than one study and computed more than one estimate for each beverage type in their studies some of these might be more influential than others in the dataset. Gallet used dummy variables for authors reporting more than one estimate to deal with the issue. Fogarty employed a different technique: he either used an arithmetical average if the study reported more than one estimate per beverage or he used the estimate from the estimation model which the author preferred. If there was no sign of preference for a specific model Fogarty included an estimate per model (again if there were more estimates per model an arithmetical average was taken). The averaging was based on the fact that estimates from different system-wide models are similar to one another and as most of the studies report results from more than 1 system-wide models they would get more weight in the meta-analysis dataset. Interestingly Fogarty did not estimate the true effect. Gallet did it in his heterogeneity analysis and he reached the a conclusion where a short-run country-wide per capita base demand which is based on a double-log equation estimated with time-series data using OLS is used as a baseline. Elasticities having the mentioned properties should then be -0,83 , -1,11 and -1,09 for beer, wine and spirits, respectively.

Wagenaar *et al.* (2009) in his later study used a more complex random effects estimation. Partial correlations between alcohol price and alcohol sales or consumption are computed for each of the studies. The partial estimates can be described as "*the standardized slope of the relationship between price/tax and consumption*" (Wagenaar *et al.* 2009). The benefit of such approach is that the studies can be easily compared regardless of the method they use for estimating the elasticity. The inverse variance is used as a measure of precision so small studies are no longer regarded as equivalent to large studies. Two important objections can still be made: the meta-analysis does not report any elasticity value that can be regarded as the true effect and publication bias is also not examined.

The model study of this meta-analysis is the one of Fogarty (2010). The inverse variance is used to weight the studies according to their precision. Several dummy variables, most of which are related to the theoretical concepts,

are used to handle heterogeneity. The mixed effects approach is used in the estimation. The meta-analysis is the only one to make pairwise comparisons in order to evaluate if different approaches to the model equation might eventually lead to statistically different results. Such comparison is reported in a table but it is not shown how large can be (and what its direction is) when another approach is used. The study is also the only one to include a time trend in its meta-regression. It is examined whether the elasticity changed across time and a quadratic trend in the samples‘ midpoints is estimated. The demand for alcohol was supposed to reach its peak in 1953 and started decreasing after that year. Such finding can be easily justified by the fact that by that time substitutes for alcohol were already well-known and still legal in most countries. After they became illegal, the demand for alcohol obviously became less elastic as the number of available substitutes dramatically dropped. Fogarty is also presenting funnel plots in order to examine publication bias. Despite their asymmetrical shape, Fogarty reports that "*there is evidence of moderate publication bias only for the beer own-price elasticity data*". Therefore estimates corrected for publication bias are not presented. The dataset coding followed the same criteria and rules as in the previous study from 2004 with the only difference that outliers were systematically removed based on an OLS regression. Both fixed and random effects estimation models are used to estimate the true effect. The weighted fixed effects and random effects means for beer are -0,26 and -0,36 respectively, for wine -0,83 and -0,57, for spirits -0,67 and -0,52. Therefore according to Fogarty the demand for beer is the least responsive to a change in price and the demand for wine is the most responsive.

The latest study done by Nelson (2014) reviews only beer own-price elasticity estimates. The between-study dependence was addressed in the same way as in the case of Fogarty (2004) (one estimate per study). A random and a fixed effects estimate are present in the study. The multilevel-mixed effects method is not employed therefore the country effect is treated only by dummy variables. Studies are weighted according to their precision and heterogeneity is treated not as accurately as in Fogarty (2010) by dummy variables, most of which are also related to theoretical concepts. However the study brings results different from the ones of Fogarty (2010) because the presence of publication bias is confirmed and corrections for it are made. The magnitude of the true effect is supposed to be between -0,19 and -0,14 which is obviously smaller than the results reported Fogarty (2010) as the issue of the presence publication bias was taken into account.

Chapter 3

The new dataset

Table 3.1: Summary statistics

	Observations	**Mean**	**Median**	**SE**	**Minimum**	**Maximum**
Beer	34	-0,65	-0,022	1,40	-5,07	0,47
Wine	28	-0,34	-0,027	0,65	-1,90	0,17
Spirits	29	-0,25	-0,023	0,44	-1,30	0,32

The following analysis is based on a dataset composed of estimates drawn from studies published between the years 2007 and 2014. The online database SCOPUS was used for the research and the following set of words was entered in order to identify the studies of interest: alcohol AND price AND elasticity. As the estimates from studies published before 2007 have already been included in previous meta-analyses only studies published after 2007 have been taken into account. The research brought 42 studies but many of them had to be removed because some key information was missing so in the end only 11 studies matched the inclusion criteria. For the purpose of the analysis each of the studies was required to contain at least one own-price elasticity estimate for one beverage category (beer, wine or spirits) and its standard error. Unfortunately many studies had only one elasticity estimate that combined the elasticity of demand for all alcohol beverages. Some of the excluded studies did not contain standard errors of the estimates and therefore appeared to be useless for the purpose of this study. Fogarty (2010) mentions that "*the intent with meta-regression analysis is to cast the net widely, and collect as much information as possible*" therefore his advice was followed and no study has been excluded because of some questionable estimation or methodology. Some of the studies reported more than one estimate per beverage category so in these cases all of the estimates reported were included in the dataset

Table 3.2: The primary studies

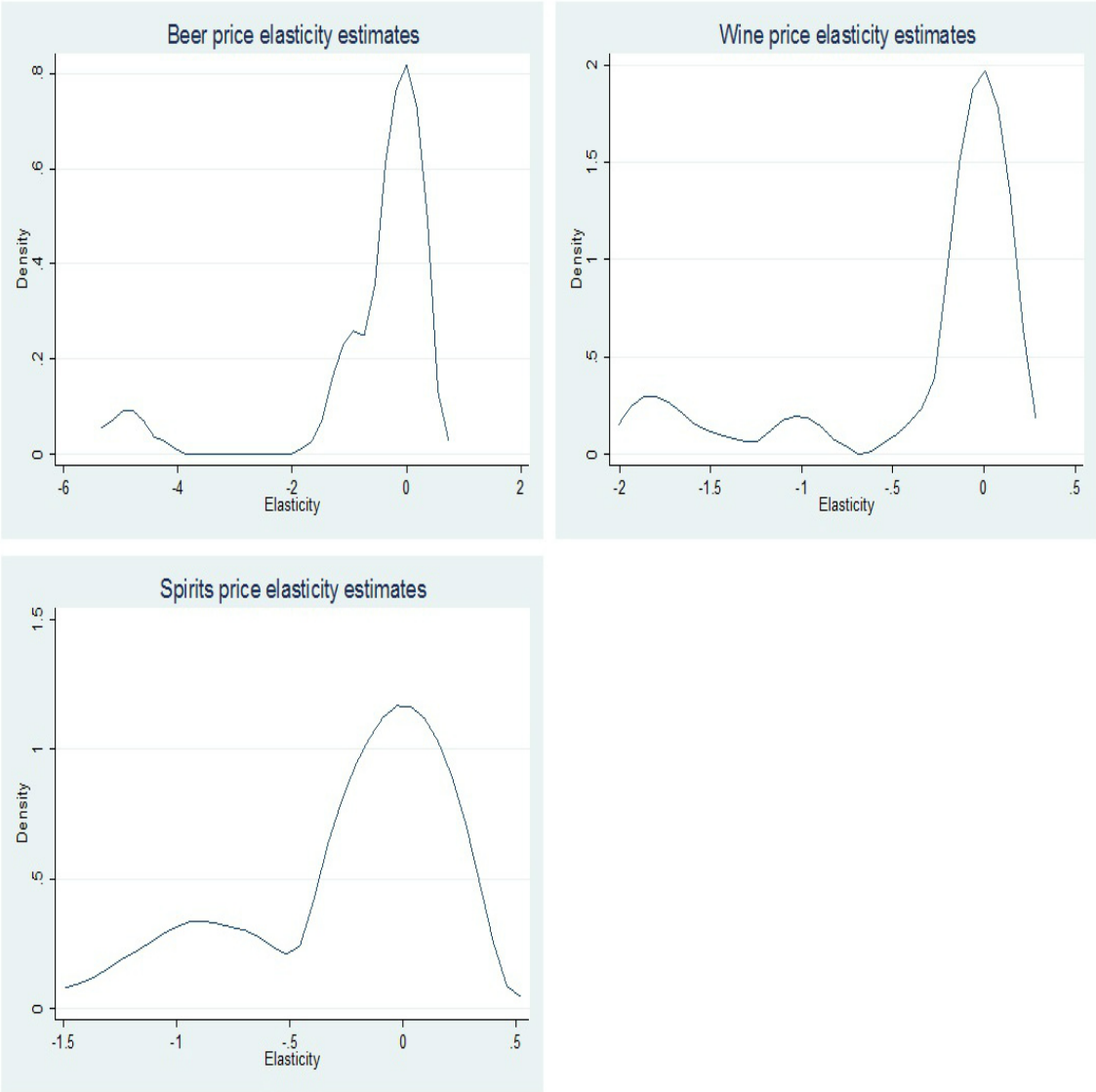
Asplund *et al.* (2007)	Bray *et al.* (2009)	La Cour & Milhøj (2009)
Ramful & Zhao (2008)	Janda *et al.* (2010)	Tian & Liu (2011)
Ruhm *et al.* (2012)	Ayyagari *et al.* (2013)	Yeh *et al.* (2013)
Goryakin *et al.* (2014)	Meng *et al.* (2014)	

The analysed studies reported 91 estimates in total where 34 correspond to the beer group, 28 wine group and 29 spirits group. The beer price-elasticity estimates go from -5,07 to 0,47 with a mean of -0,65 and a standard deviation of 1,40 , the wine elasticity estimates range from -1,90 to 0,17 with a mean of -0,34 and a standard deviation of 0,65 and the spirits elasticity estimates go from -1,30 to 0,32 with a mean of -0,25 and a standard deviation of 0,44. It is apparent from Table 3.1 that the medians of the different beverage categories are quite close to each other. On the other hand the differences between the means are much higher. The mean values reported in Fogarty (2010) are -0,44 , -0,65 and -0,73 for beer, wine and spirits respectively. Except for beer, which is more elastic, the mean elasticities in this dataset are considerably less elastic. Does it mean that less-elastic elasticities are more reported? Not necessarily, it can be due to the fact that Goryakin *et al.* (2014) reported 48 estimates in his study and many of them were very close to zero which over-weighted other estimates and drove the mean closer to zero.

Figure 3.1 shows the Epanechnikov kernel densities of the elasticity estimates for different beverage categories. It is easily noticeable that each of the categories seems to follow the normal distribution with a mean very close to zero. This hypothesis has been confirmed by a goodness of fit Chi-square test. Another interesting aspect of the kernels is the high concentration of estimates on the left side of the X axis. It is questionable whether such concentration is the cause of the heterogeneity in approaches to alcohol consumption or simply by publication bias.

The distribution is skewed in all of the cases but it is mostly apparent in the case of beer. It is also highly probable that some outliers are present in the data as the density on the left side increases quite a lot around 4. This increase is caused by the elasticity estimates picked up from the study of Bray *et al.* (2009) who estimated the own-price elasticity of different types of beer packages. It is logical to expect higher magnitudes for these estimates as the category is more specified and therefore there are more substitutes on the market. Thus it is reasonable to exclude these from the dataset as they differ too much

Figure 3.1: Epanechnikov kernel densities



from other estimates in the dataset. Wine consumption seems at first sight to indicate either heterogeneity in demands or presence of outliers as there are two increases in the density on the left side of the X axis. When comparing it to the distribution from figure 4.1 (the kernel density functions for the dataset combining Fogarty‘s and the new observations) it can be observed that the inclusion of older estimates make it even more skewed. The distribution of spirits seems to indicate that there might be two different approaches to spirits consumption: most of the estimates indicate a very inelastic demand but there is also a group indicating a more elastic demand. This hypothesis seems to be rejected by Figure 4.1 which shows that there might be only one true effect.

3.1 Publication bias

One of the key parts of each meta-analysis is the part dedicated to studying whether publication bias is present in the sample studies or not. According to Stanley (2005) publication bias, often referred as file drawer problem, is an issue that arises from the fact that statistically significant results tend to be treated more favourably. Scargle (1999) is more precise in his descriptions: "*A publication bias exists if the probability that a study reaches the literature, and is thus available for combined analysis, depends on the results of the study.*" It can be seen that the definition is even wider, thus publication bias is present when there is a dependence between the publication and the results of a study. Sometimes the researchers as well can be influenced as they can have some preconceived results. If their result is not significant or does not prove the expected effect the researcher might be motivated to change it (for instance by increasing the sample size until a better figure is obtained). Such preference for statistically significant effects and the rejection of the non-significant ones can lead to biased results when analysing the literature. The conclusions drawn may indicate a significantly larger effect than in reality. This might be the case of the alcohol consumption.

How do people react if the price of alcohol increases? Most of the people would expect a negative sign of the price-elasticity as they consider alcohol as a normal good, but what if in reality alcohol is embedded in society almost as a necessity and people are not affected by its price? The fact of reaching a zero elasticity estimate can still be explained by some social aspects of the examined population but what if positive elasticity estimates are obtained? Nelson (2014) reported that the true own-price elasticity of beer should be between -0,19 and -0,14. Thus the probability of reaching positive estimates because of the sampling error is relatively high.

If there is a great lack of reported positive estimates despite the fact that according to the sampling error they should be present it is said that type I publication bias is present in the literature. The consequences of this type of bias will make the usual estimators of the true effect excessively high. Another trend that can be often noticed in the literature is the unusual number of highly significant results that are reported. Random sampling should make significant estimates rare but as it will be seen further in the graphical analyses there is a lot of them in the alcohol-related literature. As close-to-zero and negative elasticity estimates are expected their standard errors must be small enough

so that they are significant. The easiest way to achieve significant results in this case is to remove some supposed outliers and get a higher magnitude of the effect. A change in the methodology or an enlargement of the sample can also help. Such preference for statistically significant results is called type II publication bias.

3.2 Funnel plots

Type I publication bias can be easily detected by a special type of a scatter diagram, the funnel plot. Precision is arrayed on the Y axis and the unstandardised effect on the X axis. The inverse of the standard error remains the most common measure of precision but the sample size or its square root can be also used (Stanley 2005). If publication bias is not present in the sample, the estimates should be symmetrically distributed around some mean value often called the true effect. The more precise the estimate the closer it should be to the true effect. Less precise estimates tend to have a wider spread around the true effect. This is why the shape of the plot resembles to an inversed funnel which is the reason for its name. The asymmetry of the graph can be used as an evidence of the presence of type I (also reffered as directional) publication bias in the literature. Type II publication bias is supposed to make the funnel *"hollow and excessively wide"* (Stanley 2005). This pattern is not commonly used due to the fact that excessive variation itself does not bias the magnitude of the average estimated effect (Stanley 2005). Therefore other methods will have to be used in order to identify the presence of type II publication bias.

Figure 3.2 depicts the funnel plots for the new dataset. There are two lines in each picture: a dashed one which indicates the weighted mean of the sample where the inverse of the standard error served as a weight and a continuous one which shows the true effect estimate obtained from the FAT test[1] (which is going to be discussed later on). The weighted average has been computed according to the following formula:

$$r_w = \frac{\sum_{i=1}^{n} w_i \gamma_i}{\sum_{i=1}^{n} w_i}$$

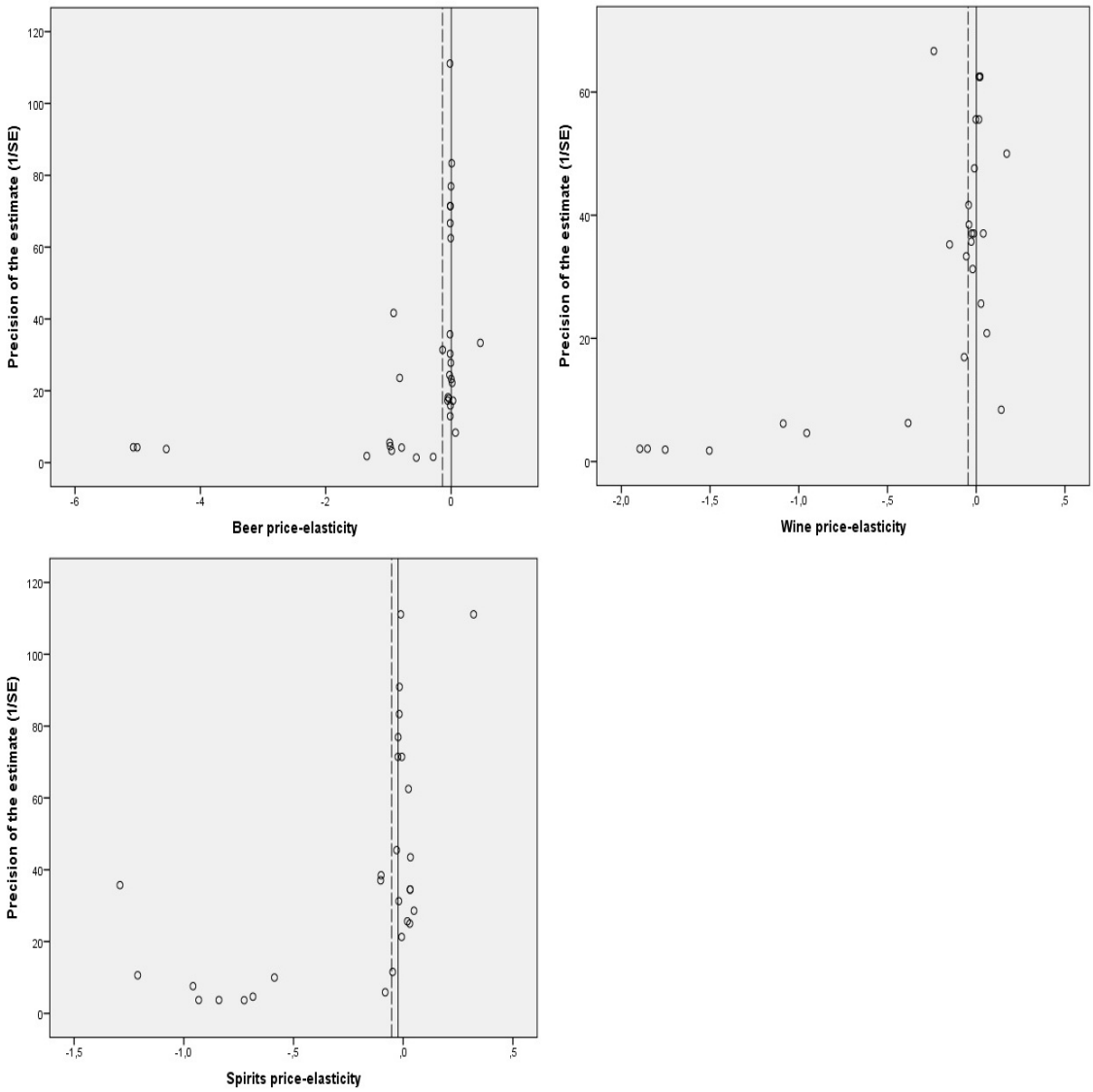
This is an asymptotically efficient estimator of the population parameter and it was used first in the study of Olkin (1985). Fogarty (2010) uses it for

[1] The FAT estimates and the weighted means have been computed without taking outliers into account.

Table 3.3: True effect estimates

	FAT estimates	**Wighted means**
Beer	0,0037	-0,1370
Wine	0,0004	-0,0461
Spirits	-0,0232	-0,0527

Figure 3.2: Funnel plots



his fixed effect approach in his meta-analysis. The true effects estimates can be found in the table 3.2

The majority of the estimates in the funnels regroup around the zero value which would lead to a hypothesis that the demand for alcoholic products is perfectly inelastic. However it should also be reminded that as some of the studies reported more than one estimate, the studies do not have the same weight in terms of number of estimates so the mean could be moved closer to zero because of that. Despite the fact that Goryakin *et al.* (2014) reported 16 estimates per category and his study is therefore highly influential most of the estimates still do not stray far from zero. Both weighted means and FAT estimates seem to represent well the axes of the funnels. None of the funnels seems to be symmetrical therefore publication bias is likely to be present. As the new dataset does not contain many observation the Galbraith plots, which examine Type II publication bias, will be omitted.

The beer funnel plot justifies the removal of the 3 outliers drawn from the study of Bray *et al.* (2009) (left side of the X axis) as their magnitudes are excessively high compared to other estimates and the elasticity they represent differs a lot from other estimates (remember that they represent elasticities for packages of beer). Spirits also appear to have an outlier. The most elastic estimate on the left side of the X axis is quite precise but it is not surrounded by other estimates that could confirm that there might be a second smaller inverted funnel (indicating that there might be 2 different demands for alcohol). Therefore it is considered as an outlier. The funnel for wine does not seem to show any outliers.

3.3 Funnel asymmetry tests and precision-effect tests

As the funnels indicated a likely presence of publication bias it is necessary to justify it by some empirical tests. If there is no publication bias in the literature, then the estimates should regroup around β_1, the true effect, and should not depend on their standard error (Stanley 2005).

$$effect_i = \beta_1 + \beta_0 Se_i + \epsilon_i$$

On the other hand if there is publication bias affecting the estimates then it will be proportional to the standard error. This comes from the fact that if there

is a preference for statistically significant estimates then according to Begg & Berlin (1988) publication bias is proportional to the inverse of the square root of the sample size, which is related to the standard error. The reason is that if there is a large standard error the researcher tries to find a larger estimate so that he gets a statistically significant result which has a higher likelihood to be published (Doucouliagos & Stanley 2009). Large studies have smaller standard errors so they do not have to report large estimates in order to be published.

The previous equation unfortunately cannot be estimated by the usual OLS method as it obviously suffers from heteroscedasticity. With an increasing amount of information the standard error converges to zero and the estimate to the true effect value. In other words estimates computed from very large sample sizes are likely to report small standard errors and are supposed to be close to the true effect. The new dataset suffers from within-study heterogeneity so the issue will have to be faced by a different estimation method. However such heterogeneity should not be an issue for the combined dataset as there is mostly one estimate per study. Therefore a simple solution is at hand: the weighted least squares method. After weighting the previous equation by the inverse of the estimate's standard error a new equation that can be estimated by OLS is obtained:

$$t_i = \beta_0 + \beta_1(1/Se_i) + e_i$$ [1]

A t-test of β_0 represents a FAT test and the estimate of β_0 indicates the direction of the bias. The estimate of β_1 from the weighted equation can then be used as an estimate of the true effect corrected for publication bias. β_1 can then be tested if significant. Such test is called the PET test. The FAT-PET estimation is also a good of estimating the true effects corrected for publication bias.

Correlation between estimates from the same study makes OLS-based estimations impossible to be used for the new dataset. In the meta-analysis for beer done by Nelson (2014) the equation for the FAT and PET tests is estimated by both random and fixed effects models. Havranek *et al.* (2012) suggests that a mixed effects estimation is more suitable for the test as it can deal with the un-balancedness of the panel (the un-balancedness consists in the unequal number of estimates reported per study). Such advantage is achieved

[1] The t-statistic should not be confused with the t-statistic used in the Galbraith plot. In this case the t-statistic is the one used for testing whether the estimate of elasticity is statistically different from zero and is equal to:

$$t_i = effect_i/Se_i$$

by giving the same weight to the studies regardless of the number of estimates they report. Another benefit of this approach, which is going to be used later in this bachelor thesis, is its flexibility: it allows the nesting of multiple random effects. Let i and j denote the estimate and study subscripts. the model equation for the new dataset will then have the following form:

$$t_{ij} = \beta_0(1/Se_{ij}) + \beta_0 + \zeta_j + \epsilon_{ij}, \quad \zeta_j|Se_{ij} \sim N(0, \psi), \quad \epsilon_{ij}|Se_{ij} \sim N(0, \theta)$$

The usual error term is now divided into two: a study-level random effect ζ_j and an estimate-level ϵ_j disturbance term. As both of the terms are assumed to be independent, their variance is therefore additive. The composed error term‘s variance can then be written as: $Var(e_{ij}) = Var(\zeta_j + \epsilon_{ij}) = \psi + \theta$, where ψ stands for the within-study variance and θ for the between study variance. The similarity with the random effects estimation is apparent, the only difference relies in the fact that a maximum likelihood estimator is used instead of a generalised least squares. In cases where ψ is close to zero the mixed effects estimation is no longer necessary and OLS can be used instead (Havranek *et al.* 2012). However this is almost never the case in meta-analyses therefore the mixed effects estimation is preferred. Most of the panels used for the meta-analyses are unbalanced. If estimated by an OLS method, the studies reporting many estimates will have a greater impact on the results than studies reporting only one. Fogarty‘s method of averaging has removed such un-balancedness caused by studies reporting many estimates per beverage category but the mixed effects still have an advantage: the approach can give equal weight to countries. This means that the country effects will be taken into account as well and each country will have the same weight regardless of the number of its observations. Thus the equation for the FAT and PET tests for the combined dataset will be the same except for the fact that the index j will denote the country subscript instead of the study.

Table 3.4: The FAT-PET‘s estimation results

	Variable	**Coefficient**	**SE**	**p-value**
Beer	1/(SE)	0,0037	0,0515	0,943
	Intercept	-2,5051	2,16	0,246
Wine	1/(SE)	0,0004	0,0264	0,988
	Intercept	-2,3486	1,1074	0,034
Spirits	1/(SE)	-0,0233	0,0085	0,006
	Intercept	1,2065	5,1162	0,814

Surprisingly the results from the FAT test indicate that type I publication bias is present only in the wine category (at a 5% level). The FAT tests in other categories fail to prove its presence. It might be because of the small number of observations and the low precision of the estimates with a greater magnitude of the effect. As it will be proved later for the combined dataset, type I publication bias is likely to be present in the literature. The PET tests' results, shown in table 3.4, in this case are even more interesting than the FATs' ones. Positive true effects for beer and wine are presented. This means that beer and wine might be considered as Giffen goods. Such finding rejects the hypothesis that alcoholic beverages are normal goods. Fortunately the PET tests reject statistical difference of these estimates from zero which suggests a perfectly inelastic demand for beer and wine. The estimated true-effect for spirits is negative, significant and close to zero which is in accordance with the author‘s expectations.

Chapter 4

The combined dataset

Table 4.1: Summary statistics

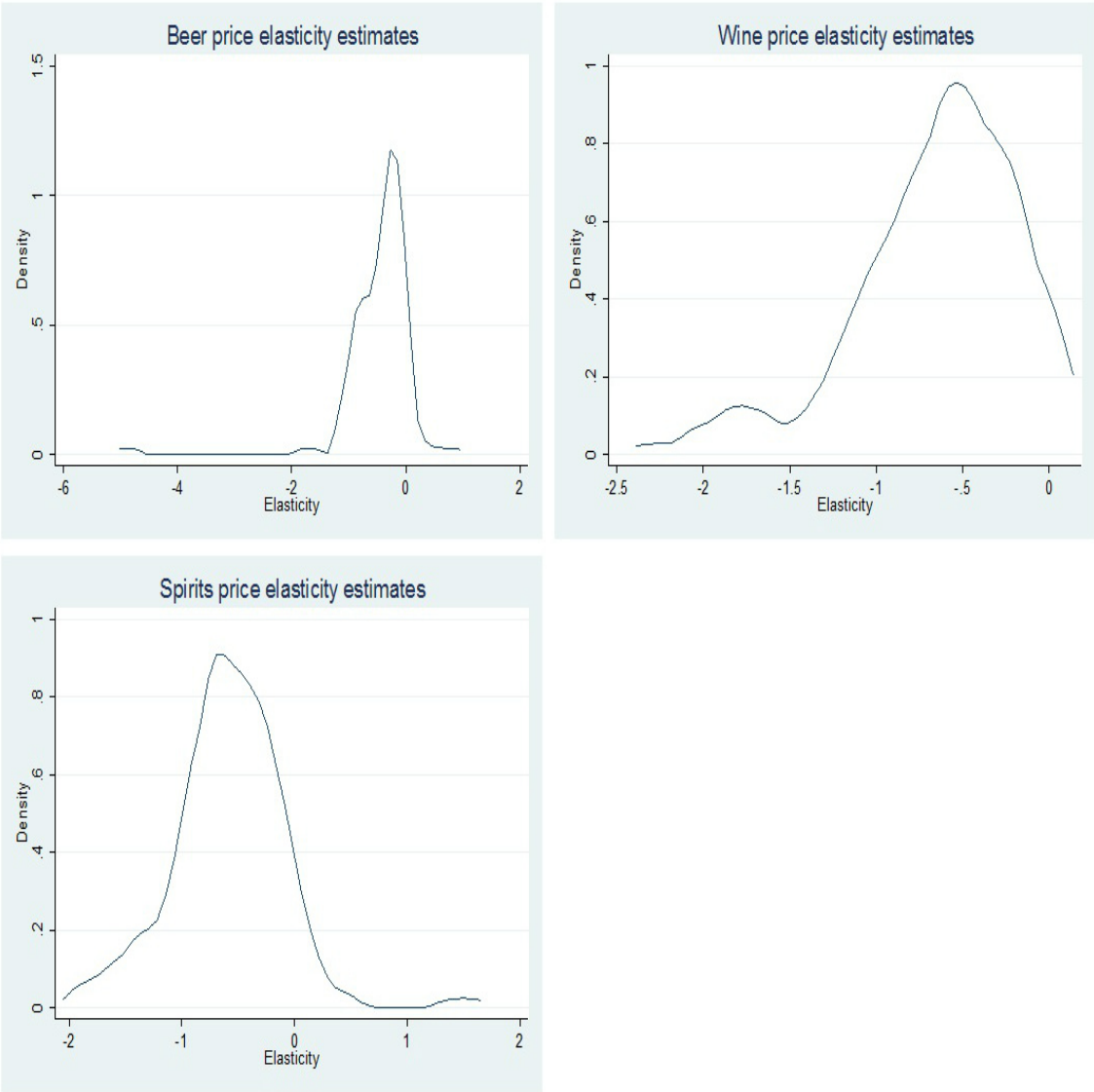
	Observations	**Mean**	**Median**	**SE**	**Minimum**	**Maximum**
Beer	95	-0,45	-0,29	0,59	-4,87	0,8
Wine	87	-0,66	-0,59	0,47	-2,25	-0,002
Spirits	93	-0,59	-0,57	0,49	-1,9	1,5

This dataset consists of two different datasets: the first one as mentioned consists of new estimates that have not been included in the meta-analysis of Fogarty (2010) and the second one is the one used by Fogarty (2010). For more in-depth analysis a larger sample is needed therefore this updated version of Fogarty‘s dataset will be used. It is worth mentioning that the new observations had to be added in accordance to Fogarty‘s methodology. If there was more than one estimate per beverage category per country in a study an arithmetical average was taken. The same was done with the standard errors. If the estimates were computed with the use of different models and the author expressed a preference for a specific approach then only the estimate obtained from it was added. If there was no preference for a model, one estimate per model was reported. Such way of coding gives each study the same weight as mostly one estimate per study and model is reported.

The dataset is composed of data from 76+11 studies where the oldest study is from the year 1949 and the latest from 2014. This sample has 275 estimates in total where 95 correspond to the beer group, 87 wine group and 93 spirits group. The beer price-elasticity estimates go from -4,87 to 0,8 with a mean of -0,45 and a standard deviation of 0,59, the wine price-elasticity estimates range from -2,25 to -0,002 with a mean of -0,66 and a standard deviation of 0,47 and

the spirits price-elasticity estimates go from -1,9 to 1,5 with a mean of -0,59 and a standard deviation of 0,49.

Figure 4.1: Epanechnikov kernel densities



In Figure 4.1 it is easily noticeable that all of the densities are strongly skewed. Apparently negative estimates tend to be published much more often than the positive ones. For this reason the graphs are skewed. This property of the distributions suggests a likely presence of type I publication bias in the estimations. The peaks of the distributions for all the beverages are further from the zero value than in the new dataset case. It seems that latest studies report estimates with a lower magnitude than older studies. Thus a time trend variable should be added in the meta-regression in order to analyse if there are

some trends in the estimation of the price-elasticities. The kernel density plots are even more skewed than the ones for the new dataset therefore a further examination of publication bias is necessary.

4.1 Funnel plots

Figure 4.2 depicts the funnel plots for the combined dataset, one for each of the beverage categories. Again a dashed line indicates the weighted mean of the sample where the inverse of the standard error served as a weight and a continuous one shows the true effect estimate obtained from the FAT test[1]. It can be easily noticed that all the graphs depict a high degree of asymmetry as only the left side of the inverted funnel is present. The funnel served also as an indicator of outliers for the dataset. Two outliers have been drawn from beer estimates and four from wine estimates.

In the case of beer the decrease in density on the positive part of the X-axis is the most apparent. The majority of the estimates with the highest precision is situated around the FAT test estimate which is -0,164. It obviously appears to be an axis of the inverted funnel. There is only a handful of positive estimates present in the sample but on the negative side of the X axis there is large amount of not very precise negative estimates which gives evidence about the presence of Type I publication bias. Positive estimates are seldom reported. Such implication drawn from the graph is in accordance with Nelson (2014) who admitted a likely presence of type I publication bias in his meta-analysis of beer elasticities.

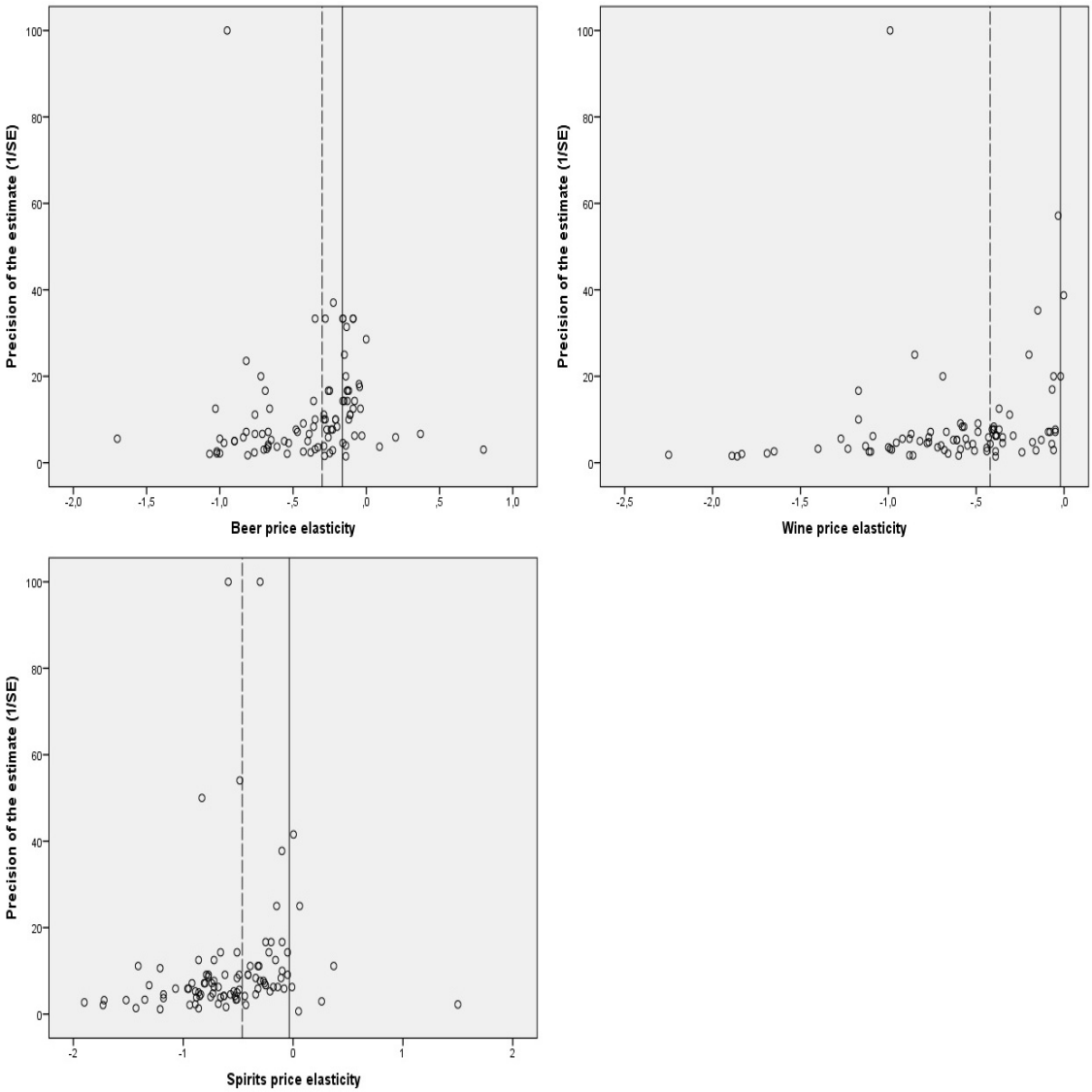
The majority of the most precise wine estimates is concentrated very close around -0,022 which again is the FAT test estimate. Despite the fact that these estimates regroup very close to zero, they are still outnumbered (even when weighted) by not very precise estimates so the weighted mean for this subcategory is -0,421. It is striking to see that there is no positive estimate for wine despite the fact that the true effect is supposed to be still relatively close to zero. Thus type I publication are most likely. Fogarty (2010) in his meta-analysis did not reach the same conclusion as he considered other estimates to represent the true effect. These values were various means: unweighed, fixed-effects and random effects ones. The problem that arises with publication bias affecting the literature consists in the fact that there are missing estimates that

[1]The beer funnel does not include one outlier (-4,87) so that the funnel can show more detail.

Table 4.2: True effect estimates

	FAT estimates	Wighted means
Beer	-0,164	-0,301
Wine	-0,022	-0,421
Spirits	-0,412 or -0,035	-0,463

Figure 4.2



cannot be included into the calculations. Therefore the means calculated from such dataset, weighted or not, must be biased because the lack of estimates will cause a shift in the computed mean. It is also questionable if such means are efficient because the yearly increase of estimates with a large magnitude and low precision (that have been set up in order to be significant) can outweigh the increase in the precise estimates from large studies. This would cause that the mean to move further away from the true effect and thus making the means asymptotically inefficient. The difference between the weighted average and the FAT estimate for wine is the highest of all of the 3 categories. If used as the true effect the weighted average would overestimate the effect by 0,39 which is almost by more than 2 times (when compared to the case where the FAT estimate would be used as the true effect)! This shows well that the weighted mean should not be taken as an estimate of the true effect as in some cases the bias can be considerably high. [1]

The funnel for spirits shows a considerable lack of positive estimates. The funnel‘s spout can be assumed to be very close to the zero value. On the other hand there are 4 very precise observations that can lead to the hypothesis of having the spout somewhere around 0,5. This shows well one of the dilemmas that arise with visual inspection: the true effect cannot be clearly identified. However if the results from the new dataset are taken into consideration the spout is more likely to be close to zero as the new dataset indicated a true effect of -0,16. Some may argue that the inclusion of the new observations has shifted the spout closer to zero so the reasoning according to the new dataset‘s true effect estimates makes no sense. It should be noted that the newly added data was treated according to the methodology of Fogarty thus averaged in many cases. Such averaging reduced the numbers of observation and the weight of the new data in the combined dataset therefore the inclusion did not affect that much the funnel‘s appearance. The removal of the 4 estimates is then considered as appropriate. The funnel then shows a high degree of asymmetry as his right-hand part is almost missing. Such shape would suggest a very likely presence of type I publication bias.

Every beverage category seems to be influenced by publication bias, however according to Stanley (2005) visual inspection is mostly subjective therefore some empirical tests will be necessary in order to confirm the hypothesis suggesting the presence of type I publication bias. Despite the apparent asymmetry

[1] Such means were used in the bachelor thesis of Sedlaříková (2012) or in the meta-analysis of Fogarty (2010)

the FAT and PET tests failed to prove it for some cases in the new dataset case so no conclusions can be drawn so far. A great drop in the magnitude of the estimated true effects can be noticed when compared to the ones from the study of (Leung & Phelps 1993) who reached the results -0,3, -1,0, and -1,5 for beer, wine and spirits respectively. Such a comparison suggests examining further possible time trends in the research.

4.2 Galbraith Plots

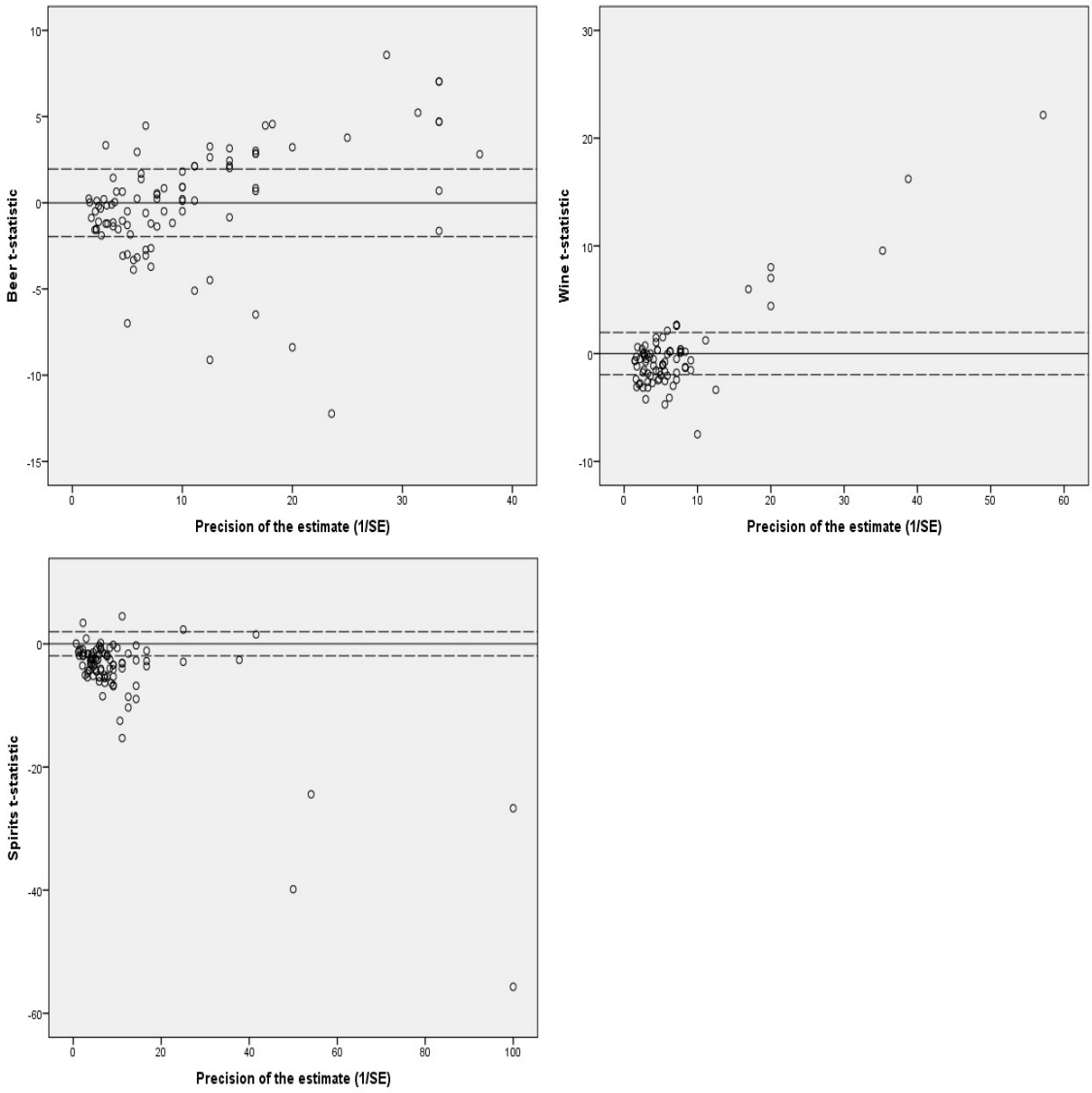
The Galbraith plot is a graphical instrument designated for detecting the presence of type II publication bias. Such bias is caused by the preference of statistically significant effects regardless of their direction (Stanley 2005). The main idea behind the test consists in the fact that the t-statistic should not exceed 1,96 in more than 5% of the cases. The t-statistic is defined as $t_i = |(effect_i - TE)/Se_i|$, where TE stands for the true effect and can be estimated by the FAT or FAIVE methods. In areas where there are many studies available a simple average of the largest studies can also become a suitable estimate of the TE (Stanley 2005). Unfortunately for alcohol price elasticity this is not the case. The Galbraith plot is obtained by plotting the t-statistic on the vertical axis and the inverse of the standard error on the horizontal axis. The resemblance to the funnel plot is worth mentioning, (Stanley 2005) describes it as "*a funnel graph rotated 90° and adjusted to remove its obvious heteroscedasticity*". In the case of a random effect equal to zero (not affected by type II publication bias) the estimates should be randomly distributed around zero without any relation to precision. In other words more than 5% of the total estimates should not be present within the (-1,96 ; 1,96) interval. None of the previous meta-analyses used the Galbraith plot.

The following figure 4.3 shows the Galbraith plots for each of the beverage categories. The true effect estimate for each of the beverages was obtained from the FAT test. The dashed lines represent the -1,96 and 1,96 bounds, the continuous one zero. As it is apparent from the picture type II publication bias is likely to affect the literature. At least more than 30% of the estimates in each category fall within the (-1,96;1,96) band. [1]. In the cases of beer and wine the majority of the estimates fall within the interval. Such aspect of the data clearly indicates preference for statistically significant results. In other words

[1] To be more specific 56%. 61% and 32% for beer, wine and spirits respectively.

the Galbraith plots show evidence of the presence of type II publication bias in every beverage category.

Figure 4.3: Galbraith plots



4.3 Funnel asymmetry tests and precision-effect tests

The equation for the FAT and PET tests can be either estimated by the mixed-effects or random effects method so that the country effect is taken into account. The mixed-effects method was again chosen for its better suitability. The model

used for the estimation has already been described in the previous section 3.3. The results of the estimations are depicted in the following table 4.3.

Table 4.3: The FAT-PET's estimation results

	Variable	**Coefficient**	**SE**	**p-value**
Beer	1/(SE)	-0,1636	0,0355	0,000
	Intercept	-1,4763	0,4979	0,003
Wine	1/(SE)	-0,0215	0,0295	0,466
	Intercept	-2,8784	0,321	0,000
Spirits	1/(SE)	-0,0353	0,0475	0,457
	Intercept	-3,216	0,5767	0,000

The results of the FAT tests in table 4.3 are not surprising: all of the categories show a highly significant β_0 coefficient (p-value $< 0,01$). In other words type I publication bias is present in the literature. Although the FAT tests were positive the PET tests' results differ. The estimated elasticity for beer is significant (at a 1% level). When compared to Nelson (2014), who reported the beer "*mean price elasticities in the range -0,14 to -0,19*", the estimated true effect -0,1636 seems to be in accordance with this finding (it even represents almost the mid-point of the interval). In the case of wine the PET failed to reject to null hypothesis therefore the estimate is not statistically different from zero. The lack of significance might be caused by the fact that the spread of the estimates is very wide and the estimated effect is very close to zero. The PET test for spirits also indicates that the estimate is not statistically different from zero.

Chapter 5

Meta regression - heterogeneity analysis

As mentioned previously the FAT test represents a reliable way how to estimate the population true effect. However such estimation does not consider the fact that the authors employ various forms of models and different types of data that can lead to different results. This is the reason why heterogeneity of the data should be examined. In other words the following part is going to test whether employing different techniques has an impact on the magnitude of the results. As heterogeneity is being examined, only one equation will be estimated. Such estimation will require the step of adding the beverage-level in the panel. Not all of the variables from the study of Fogarty (2010) will be included in the equation as the aspects they represent could not be distinctly identified from the studies. It is the case of the variables specifying the theoretical concept: Marshallian and Hicksian elasticity estimates, conditional and unconditional demand or short-run and long-run estimates.

First of all it will be examined if the data and equation types have a direct impact on the magnitude of the estimates. An updated form of the model for the FAT test will be used for this purpose. The added explanatory variables will be therefore weighted by the inverse of the standard error. Then the economics research cycle hypothesis will be examined. Such hypothesis, stated by (Goldfarb 1995), suggests that studies follow popular trends in research. This means that the early findings are supposed to start confirming a newly stated hypothesis but after some time, when the hypothesis is becoming less popular, scientists become more sceptical, the trend reverses and results rejecting the hypothesis appear more frequently. The trend can also be opposite − the hy-

pothesis can first be rejected and then be confirmed. Thus a quadratic function of the year of publication is used to estimate such trend in the t-statistics of the estimates (Polák 2011). As the year of the publication does not have a direct impact on the magnitude of the estimate, it will not have to be weighted. After that it will be examined if there is a trend in the elasticities. For this analysis the midpoint of the dataset will be used. Similarly as for the economics research cycle hypothesis a quadratic form of the trend will be estimated. Since the elasticity estimates (and not the t-statistics) are expected to follow such trend, the trend variables will have to be weighted.

The equation is estimated by the mixed-effects method as Nelson & Kennedy (2009) suggested that a random effects method "*should be employed unless a very strong case can be made for its inappropriateness*". Heterogeneity is very likely to be present since the approach to the alcohol beverage categories varies from country to country. As the panel used for the meta-analysis is unbalanced (the number of estimates varies, depending on country and beverage) the mixed-effects multilevel method will be used instead of the random effects. Such estimation method will allow to include 3 different levels in the estimation. A similar model as the one for the FAT and PET tests will be used. Let b denote the beverage category, c the country and i the estimate subscripts. The model will then be:

$$t_{bci} = \beta_0 + B_1(1/Se_{bci}) + \sum_{t=1}^{T} \frac{\delta_t S_{bcit}}{Se_{bci}} + e_{bc} + u_{bci}, \quad (i = 1, 2, ...N),$$

$$e_{bc}|Se(e)_{bci} \sim N(0, \theta) \quad u_{bci}|Se(e)_{bci} \sim N(0, \psi)$$

where S_{ijk} are the variables that are summed up in the following table 5.1. The usual error term is divided into two: e_{bc} denotes the random effects and u_{bci} stands for the estimate level disturbance term. The error terms are assumed to be independent therefore their variances are additive.

Table 5.1: The Variables

Simple OLS, Time-series, Cross-sectional, Panel, System-wide	These dummy variables indicate the various type of data and estimation approaches used in the estimation. The sytem-wide dummy variable accounts for system-wide approaches in the estimation. (Rotterdam, AIDS, CBS and NBR). (They are equal to 1 when the specific estimation was used.)
Quart, Month and Daily	These dummy variables account for the different frequency in the observation. (They are equal to 1 when the specific frequency was used.)
Dynamic	The Dynamic dummy informs whether the addictive nature of alcohol has been taken into account in the estimation. (It is equal to 1 if the additive nature has beeb accounted for.)
Published, Published2	These variables represent the publication date and the publication date to the power of 2.
Midpoint, Midpoint2	These variables stand for the midpoint year of the dataset of the study and the midpoint year to the power of 2.

5.1 Results

Table 5.2: Heterogeneity analysis

	Coefficient	**SE**	**p-value**
1/SE	-0,0878	0,0401	0,03
Quart	0,0601	0,0501	0,23
Month	-0,1737	0,0620	0,01
Daily	-0,0405	0,0657	0,54
Time-series	-0,0883	0,0504	0,08
Cross-sectional	-0,3727	0,0714	0,00
Panel	0,1878	0,0552	0,00
System-wide	-0,0172	0,0376	0,65
Dynamic	-0,1275	0,0486	0,01
Intercept	-2,2050	0,3187	0,00

Table 5.2 shows the results from the heterogeneity analysis. Estimates computed from a single-OLS equation using yearly data served as the baseline. The variables accounting for frequency in Table 5.2 can be used only for a comparison with the yearly observations. For instance only monthly collected data do bring a statistically different estimate (at a 5% level) and the difference is approximately -0,17.This is why the equation had to be estimated several times to enable pairwise comparisons of the frequency and data-type dummy variables.

Table 5.3: Frequency analysis

	Year	Quart	Month	Daily
Year	-			
Quart	0,06012	-		
Month	-0,1737**	-0,2338**	-	
Daily	-0,0405	-0,1006	0,13323*	-

*Significant at a 10% level, ** significant at a 5%

The variables for the type of data similarly as the frequency data need to be compared pairwise. Table 5.3 shows the magnitude of the effect caused by the change of using the data in the first column instead of the data in the first array. For instance if monthly data is used instead of yearly data, the resulting price-elasticity estimate will decrease by approximately 0,17. The comparison of the significant estimates from table 5.3 leads to the conclusion that the largest estimates are calculated from daily and yearly collected data and the smallest estimates from monthly collected data. In absolute terms this would

mean that for negative estimates the largest reported magnitudes are expected to be brought by monthly collected data and the smallest magnitudes by daily and yearly data. The comparison of magnitudes is done for negative estimates as the price-elasticities of alcoholic beverages is more likely to be negative.

The comparison between the results from different estimation models was done in the same way as for the data frequencies. The results depicted in table 10 lead to the conclusion that for negative estimates panel data bring the smallest results in magnitude. The largest magnitudes are obtained when using cross-sectional data. The only thing that is known about the system-wide approach is that it should lead to estimates with a larger magnitude than panel data, similarly as the single OLS and time-series approaches.

Table 5.4: Estimation models analysis

	Simple OLS	Time-series	Cross-sectional	Panel	System-wide
Simple OLS	-				
Time-series	-0,088*	-			
Cross-sectional	-0,373**	-0,399**	-		
Panel	0,188**	0,240**	0,240**	-	
System-wide	-0,017	0,090	0,090	-0,106	-

*Significant at a 10% level, ** significant at a 5% level

The publication date variables were included in the equation where single-OLS equation using yearly data served as the baseline. As table 5.5 shows the trend is highly significant therefore there is evidence supporting the economics research cycle hypothesis. The peak of the quadratic function is in 1983. This would mean that most of the t-statistics kept increasing by that time and after that the scientists slowly became more sceptical and t-statistics lower in magnitude started to appear more often.

The previous analysis proved that the estimates' years of publication follow a time trend. Now it will be examined if the midpoints of the datasets used for the estimations of the elasticities also follow such trend. An evolution in the approach to alcohol can be expected because of the fast development of drugs during the 20th century. History would lead to the hypothesis of a quadratic trend: the discovery of new substitutes for alcohol lead to an increase of the own-price elasticity and the following steps against drug usage made the elasticity values drop. The results of the analysis are reported in table 5.6. The p-values of the Sample date and Sample date2 variables are 0,014 so there is no doubt about their joint significance. The estimates for Published and

Table 5.5: Economics research cycle hypothesis

	Coefficient	**Standard error**	**p-value**
1/SE	-0,0352	0,0397	0,376
Year	0,0541	0,0489	0,269
Month	-0,1373	0,0593	0,020
Daily	0,0339	0,0636	0,594
Time-series	-0,0984	0,0479	0,040
Cross-sectional	-0,4427	0,0705	0,000
Panel	0,1883	0,0533	0,000
System-wide	-0,0881	0,0383	0,021
Dynamic	-0,1573	0,0476	0,001
Published	14,2811	2,7858	0,000
Published2	-0,0036	0,0007	0,000
Intercept	-14191	2767	0,000

Published2 variables changed a bit making their estimated trend's function a bit flatter but its peak remained unchanged.

Table 5.6: The trends in the elasticities

	Coef.	**SE**	**p-value**
1/SE	-568,221	170,3303	0,001
Year	-0,10894	0,067419	0,106
Month	-0,02647	0,082818	0,749
Daily	-0,1866	0,050191	0
Time-series	-0,07707	0,047655	0,106
Cross-sectional	-0,5604	0,080376	0
Panel	0,298304	0,066917	0
System-wide	-0,1156	0,038785	0,003
Dynamic	-0,19289	0,048432	0
Published	8,330225	3,407196	0,014
Published2	-0,0021	0,000857	0,014
Sample date	0,58032	0,17385	0,001
Sample date2	-0,00015	4,44E-05	0,001
Intercept	-8282,38	3387,259	0,014

The inclusion of the time trends variables shows that the elasticity of demand for alcohol developed across time and its magnitude (in absolute terms) has been decreasing and making the demand less and less elastic since 1934.

The second model with the results from table 5.6 did not suffer from multicollinearity despite the fact that the published and midpoint variables were expected to be highly correlated. The inclusion of the 2 midpoint variables did not change too much the trend estimated for the economics research cy-

cle hypothesis, the peak of the function remained the same only the function became a little bit more flatter. The expected high correlation should have caused either multicollinearity problems or at least a high degree of similarity of the 2 trends. The trend for the economics research cycle hypothesis was expected to be a similar version of the trend in elasticities with a lag of 10 to 20 years. However the heterogeneity analysis showed different results: the reported t-statistics were supposed to reach their peak in 1983 which is almost a 50-years lag. Also the trend estimated by the midpoint variables is much flatter than the trend of the published variables. Such differences indicate that the variables are not that correlated as expected. These properties of the time trends indicate a likely presence of trends in the published elasticities.

Chapter 6

Conclusion

The aim of this bachelor thesis was to update and analyze deeper the data of Fogarty (2010).Unfortunately all of the variables could not be fully updated as for some studies the aspects they represented were not specified.

This meta-analysis, in contrast to the one of Fogarty (2010), has shown that publication bias is present in the literature. Its presence was proved both graphically and empirically. Its impact on the magnitudes is shown to be relatively high when compared to the results of Fogarty (2010). The elasticities calculated from the combined dataset are -0,16, -0,02 and -0,04 for beer, wine and spirits, respectively. The values for the new dataset are: 0, 0, and -0,02 (for beer, wine and spirits, respectively). The fixed effects method in the study of Fogarty (2010) leads to the values of: -0,36 -0,57 and-0,52 (for beer, wine and spirits, respectively). The findings of this analysis could not prove entirely that the own-price elasticity is negative and close to zero. Statistically significant results were obtained only for spirits from the new dataset and for beer from the combined dataset.

Another interesting finding is that the price elasticity of demand for alcohol evolved across time. Evidence supporting the economics research cycle hypothesis also appeared to be significant. This would mean that despite a little change in the elasticity, the analysis showed that there was a period when it was "popular" to report large t-statistics. According to the model after 1983 the t-statistics should decrease and gradually start to reject the hypothesis of a statistically significant effect. Such trend can be the explanation of the very small positive PET estimates obtained from the new dataset.

The heterogeneity analysis indicated that some types of data can affect the magnitude of the results. Such an analysis can help researchers in the choice of

theoretical approaches for their estimations as it indicates whether the use of specific techniques has an impact on the result or not. Since publication bias was proved to amplify the magnitudes of the estimates, the findings lead to a recommendation to use daily or yearly collected data as these are supposed to yield the smallest magnitudes of the elasticities. It is expected that yearly data will be preferred as they are not as costly to obtain as the daily data. The fact that they are often available at statistics bureaux of many countries makes them easy to obtain. Similarly as the frequency analysis showed the suitability of the yearly and daily frequencies the estimation models analysis indicated that panel data are the most suitable for the estimation. The inclusion of the addictive nature of alcohol appeared to have a significant effect on the estimates. However as it has not been discovered yet how to implement the assumption into the estimation methods that are mostly used nowadays (AIDS or Rotterdam) it does not have to be included in the models.

The findings about the elasticities indicate that a change in the price of alcohol almost does not affect the demand for alcohol as only 2 out of 6 estimates obtained are significantly different from zero. Such conclusion brings new evidence about the demand for alcohol which was considered to be (almost perfectly) elastic almost 20 years ago! In contrast to that now the demand can be considered inelastic or very close to it.

The implication for the taxation is not straightforward. Higher prices of alcohol can lead to an illegal production similarly as in Russia where a higher taxation in order to reduce the consumption led to an increase in the production of moonshine. Such an increase can then lead to an even worse situation where dangerous alcoholic beverages are consumed. On the other hand there are countries, in Scandinavia for instance, where high taxation can be a solution to bad externalities an increased consumption of alcohol yields. Therefore several other social factors have to be considered when making decisions based on the own-price elasticity of alcohol. Which these factors are can be analysed further in another thesis.

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Appendix A

Proof 1

First of all let's show that a normal good is a common good. Consider the Slutsky equation, where the change in price is negative, p stands for the price, u for utility and M for income:

$$\overbrace{\frac{\delta x_i(p_i;M)}{\delta p_i}}^{<0\text{ (common good)}} = \overbrace{\frac{\delta h_i(p_i;u)}{\delta p_i}}^{<0} - \overbrace{\frac{\delta x_i(p_i;M)}{\delta M}}^{>0\text{ (normal good)}} \overbrace{x_i(p_i;M)}^{\geq 0}$$

The implication that a normal good must be also a common good is straightforward: a negative result is obtained after an addition of 2 negative numbers (given the fact that the Hicksian demand always has a negative slope). To prove that the Marshallian price elasticities are more elastic that the Hicksian ones the first equation need to be multiplied by $\frac{p_i}{x_i}$:

$$\underbrace{\frac{\overbrace{\frac{\delta h_i(p_i;u)}{\delta p_i}}^{<0}}{\frac{x_i}{p_i}}}_{\text{Hicksian own-price elasticity}} = \underbrace{\frac{\overbrace{\frac{\delta x_i(p_i;M)}{\delta p_i}}^{<0\text{ (common good)}}}{\frac{x_i}{p_i}}}_{\text{Marshallian own-price elasticity}} + \underbrace{\frac{\overbrace{\frac{\delta x_i(p_i;M)}{\delta M}}^{>0\text{ (normal good)}}}{\frac{x_i}{p_i}}}_{\text{Income elasticity}} \underbrace{\overbrace{x_i(p_i;M)}^{\geq 0}}_{\text{Marshallian demand}}$$