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The demand for alcohol: a meta-analysis of elasticities*

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Numerous studies have estimated elasticities of alcohol demand using different procedures. Because of widespread differences in demand estimates, however, it is difficult to synthesise the literature into coherent meaning. This study improves our understanding of alcohol demand by reporting results from a meta-analysis of 132 studies. Specifically, regressing estimated price, income and advertising elasticities of alcohol on variables accounting for study characteristics, we find alcohol elasticities to be particularly sensitive to demand specification, data issues and various estimation methods. Furthermore, compared to other alcoholic beverages, beer elasticities tend to be more inelastic.

Key words: alcohol demand, elasticity, meta-analysis.

1. Introduction

In light of the health consequences associated with excessive drinking, policy-makers rely on a variety of tools (including, amongst others, taxation and restraints on advertising) to curb alcohol consumption. However, with the efficacy of demand-reducing policies tied to the elasticities of demand, it is an onerous task to choose elasticity values upon which policy decisions are based, for the myriad of elasticity estimates in the literature confounds the decision-making process. In the case of tax-based policies, for example, while we might expect its addictive nature to lead alcohol to be price inelastic (and hence relatively unresponsive to changes in tax rates), the literature reports both inelastic and elastic estimates of the price elasticity. Among other factors, such a range of price elasticity estimates could be tied to the degree of aggregation (i.e. modelling demand at the firm-level or product-level may magnify the price elasticity estimate).

Given the volume and heterogeneity of elasticity estimates, this paper sifts through the literature to uncover factors that affect the estimated price, income and advertising elasticities of alcohol demand. Specifically, similar to meta-analyses of gasoline (e.g. Espey 1998) and cigarette demand (e.g. Gallet and List 2003), we survey the literature and treat the estimated elasticities as dependent variables in a meta-regression. The elasticities are then regressed upon a series of variables that account for study attributes. Based on our

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results, the policymaker is better informed of the characteristics of studies that induce higher or lower elasticity estimates; such that, if an adopted elasticity is challenged on the basis of empirical specification, our results highlight the degree to which modelling characteristics influence the elasticity estimate.

Specific questions to be addressed by our meta-analysis include: (i) Do elasticity estimates differ across types of alcohol? (ii) Are short-run and long-run elasticity estimates different? (iii) Does specification of the demand equation influence the estimated elasticities? (iv) Are elasticity estimates sensitive to differences in data across studies? (v) Does the method of estimation affect elasticity estimates? and (vi) since later studies seek to answer questions raised by earlier studies, does the year of publication, as well as the quality of publication outlet, influence the elasticity estimates?

The remainder of the paper is organised as follows. Section 2 discusses the data used in the meta-analysis. Section 3 presents the meta-regression procedure, while the estimation results are given in Section 4. A conclusion is provided in Section 5.

2. Data

Several steps were taken to compile a list of studies that have estimated price, income and/or advertising elasticities of alcohol demand. Specifically, an initial search using *EconLit* led to numerous studies. The reference sections of these studies, as well as the reference sections of several qualitative literature reviews (e.g. Lau 1975; Ornstein and Levy 1983; Smart 1988; Godfrey 1990; Leung and Phelps 1993; Saffer 1995; Cook and Moore 2000; Larivière *et al*. 2000), were then searched for further studies. Finally, a search of the Internet led to some additional studies. In total, 132 studies were included in the meta-analysis (see Table 1), which provided 1172 estimated price elasticities, 1014 estimated income elasticities and 322 estimated advertising elasticities.

Table 2 provides a variety of information on the elasticity estimates. For instance, across all observations the median price (income) elasticity estimate equals –0.535 (0.690). Also, since the median advertising elasticity estimate (0.029) is quite small, this lends support to those studies (e.g. Calfee and

Table 1 Studies included in the meta-analysis†

Author(s)	Year published	Author(s)	Year published
Adrian and Ferguson	1987	Gallet and List	1998
Ahtola, Ekhom and Somervuori	1986	Gallet	1999
Andrikopoulos, Brox and Carvalho	1997	Gao, Wailes and Cramer	1995
Andrikopoulos and Loizides	2000	Godfrey	1988
Angulo, Gil and Gracia	2001	Goel and Morey	1995
Atkinson, Gomulka and Stern	1990	Grabowski	1976
Baltagi and Griffin	1995	Grossman, Chaloupka and Sirtalan	1998
Baltagi and Griffin	2002	Grossman and Markowitz	1999
Barsby and Marshall	1977	Gruber, Sen and Stabile	2002
Bask and Melkersson	2001	Heien and Pompelli	1989

Table 1 *Continued*

Author(s)	Year published	Author(s)	Year published
Bentzen, Eriksson and Smith	1999	Hogarty and Elzinga	1972
Bieliñska-Kwapisz and Young	2001	Holm	1995
Blake and Nied	1997	Huang	2003
Blaylock and Blissard	1993	Johnson and Oksanen	1974
Blaylock and Blissard	1993	Johnson and Oksanen	1977
Bourgeois and Barnes	1979	Johnson	1985
Buccola and VanderZanden	1997	Johnson, Oksanen, Veall and Fretz	1992
Butter, Delifotis and Koning	1997	Jones	1989
Calfee and Scheraga	1994	Kenkel	1996
Chang, Griffith and Bettington	2002	Larivière, Larue and Chalfant	2000
Clements and Johnson	1983	Labys	1976
Clements and Selvanathan	1987	Larue, Ker and MacKinnon	1991
Clements and Selvanathan	1988	Lau	1975
Clements and Selvanathan	1991	Lee and Tremblay	1992
Clements and Selvanathan	1995	Leppänen, Sullström and Suoniemi	2001
Clements, Yang and Zheng	1997	Levy and Sheflin	1983
Comanor and Wilson	1974	Levy and Sheflin	1985
Conrad	1989	Lynk	1984
Cook and Tauchen	1982	Malmquist	1948
Coulson, Moran and Nelson	2001	Manning, Blumberg and Moulton	1995
Crawford, Smith and Tanner	1999	Mast, Benson and Rasmussen	1999
Crooks	1989	Mayo	2000
Decker and Schwartz	2000	McCornac and Filante	1984
Duffy	1982	McGahan	1995
Duffy	1982	McGuinness	1980
Duffy	1983	McGuinness	1983
Duffy	1987	Miller and Roberts	1972
Duffy	1990	Moosa and Baxter	2002
Duffy	1991	Musgrave and Stern	1988
Duffy	1995	Nayga and Capps	1994
Duffy	2001	Nelson	1990
Duffy	2002	Nelson	1997
Florkowski and McNamara	1992	Nelson	1999
Franke and Wilcox	1987	Nelson	2003
Freeman	1999	Nelson and Moran	1995
Freeman	2000	Nelson and Young	2001
Nerlove and Addison	1958	Smith	1976
Niskanen	1962	Spurry	1999
Ornstein and Hanssens	1985	Stone	1945
Owen	1979	Su and Yen	2000
Pacula	1998	Swidler	1986
Pagoulatos and Sorensen	1986	Tegene	1990
Penm	1988	Thom	1984
Pompelli and Heien	1991	Tsolakis, Riethmuller and Watts	1983
Prest	1949	Uri	1986
Saffer	2000	Wales	1968
Saffer and Dave	2002	Walsh	1982
Salisu and Balasubramanyam	1997	Walsh and Walsh	1970
Sander	1999	Wang and Jensen	1997
Sass and Saurman	1993	Wilkinson	1987
Sass and Saurman	2001	Yamada, Kendrix and Yamada	1993
Schweitzer, Intrilligator and Salehi	1983	Yen	1994
Selvanathan	1988	Yen	1995
Selvanathan	1989	Yen and Jensen	1996
Selvanathan	1991	Yu and Chen	1998
Selvanathan	1995	Zardkoohi and Sheer	1984

†Complete references of the 132 studies are available upon request.

Table 2 Frequency of variables included in the elasticity equations

		Number of observations (median elasticity)†		
Category	Variable	*Price*	*Income*	*Advertising*
Elasticity estimate:	Short-run	1024 (–0.518)	901 (0.676)	271 (0.029)
	Long-run	148 (–0.816)	113 (0.860)	51 (0.029)
Beverage:	Beer	315 (–0.360)	278 (0.394)	95 (0.020)
	Wine	300 (–0.700)	240 (1.100)	83 (0.007)
	Spirits	294 (–0.679)	245 (1.000)	81 (0.070)
	Alcohol	263 (–0.497)	250 (0.499)	63 (0.032)
Specification:	Functional form:			
	Linear	160 (–0.595)	133 (0.190)	19 (0.130)
	Double-log	318 (–0.642)	339 (0.487)	72 (0.025)
	Semi-log	239 (–0.470)	225 (0.600)	19 (0.027)
	AIDS	166 (–0.820)	104 (1.010)	104 (0.007)
	Rotterdam	251 (–0.430)	187 (1.050)	94 (1.049)
	Hybrid	38 (–0.296)	26 (1.116)	14 (0.012)
	Addiction:			
	Myopic	272 (–0.668)	241 (0.383)	106 (0.012)
	Rational	28 (–0.769)	0	0
	Other issues:			
	Smuggling	68 (–0.722)	49 (0.550)	0
	Hurdle	48 (–0.556)	51 (0.262)	0
	Tobacco price	54 (–0.563)	46 (0.995)	21 (0.014)
	Other alcohol price	672 (–0.529)	508 (0.860)	238 (0.025)
Data:	Quantity:			
	Per capita	931 (–0.519)	827 (0.710)	285 (0.029)
	Total	241 (–0.680)	187 (0.406)	37 (0.030)
	Ethanol-equivalent	293 (–0.390)	287 (0.481)	62 (0.025)
	Time-series	913 (–0.540)	732 (0.807)	322 (0.029)
	Cross-sectional	84 (–0.683)	90 (0.269)	0
	Panel	175 (–0.474)	192 (0.308)	0
	Aggregation:			
	Country	699 (–0.490)	581 (0.768)	241 (0.034)
	State/Province	375 (–0.671)	359 (0.572)	81 (0.007)
	Individual	87 (–0.640)	74 (0.213)	0
	Firm	11 (–1.207)	0	0
	Gender:			
	Men	1 (–0.509)	2 (0.193)	0
	Women	1 (–0.750)	11 (0.120)	0
	Age:			
	Adult	22 (–0.556)	30 (0.267)	0
	Young Adult	13 (–0.386)	4 (0.328)	0
	Teen	1 (1.167)	2 (–0.001)	0
Estimation:	Method:			
	OLS	547 (–0.610)	526 (0.620)	93 (0.037)
	2SLS	77 (–0.644)	53 (0.667)	31 (0.080)
	3SLS	19 (–0.794)	19 (1.423)	16 (0.103)
	FIML	111 (–0.373)	82 (0.836)	39 (0.025)
	MLE	181 (–0.430)	136 (0.730)	44 (0.044)
	SUR	158 (–0.645)	116 (0.837)	97 (0.007)
	GMM	4 (–2.215)	0	0
	GLS	75 (–0.370)	82 (0.332)	2 (0.060)
	Corrections:			
	Serial correlation	67 (–0.680)	68 (0.620)	12 (0.030)
	Heteroskedasticity	66 (–0.453)	78 (0.264)	12 (0.019)
	Multicollinearity	3 (–0.279)	3 (0.553)	0
Publication:	Top 36 journal	187 (–0.597)	195 (0.499)	13 (0.013)
Total observations:		1172 (–0.535)	1014 (0.690)	322 (0.029)

†Median elasticities correspond to the median across all elasticities reported for a particular variable. For example, across the 1024 short-run price elasticities, the median equals −0.518; whereas across all 1172 observations the median equals −0.535.

Scheraga 1994; Nelson 1999) that argue advertising bans have little impact on alcohol demand. As such, similar to several studies of the cigarette market (e.g. Barnett *et al*. 1995; Gallet 2003), which also find a similar impact of advertising on demand, it may be that alcohol advertising is a strategic variable on the supply side of the market and plays an important role in determining the nature of competition in the market for alcohol. Nonetheless, with the standard deviations of the price (1.08), income (0.90) and advertising (0.16) elasticities being relatively large, coupled with non-zero correlation coefficients for the price-income elasticity pair (–0.30), price-advertising elasticity pair (0.18) and income-advertising elasticity pair (–0.11), this suggests a 'one size fits all' approach may be inappropriate, for study attributes may play a common part in determining elasticity estimates.

To facilitate our understanding of differences in elasticities across the literature, we collected information on several common traits of studies, which cover a broad range of attributes, including the type of elasticity estimate, the beverage to which the elasticity applies, the specification of demand, the nature of the data, estimation techniques utilised, year of publication and quality of the publication outlet (measured by whether or not the estimate comes from a study appearing in a journal listed among the top 36 economics journals reported by Scott and Mitias (1996)). Table 2 shows that most of the elasticities are short-run estimates, and in the case of the price and income elasticities, at the median the short-run estimates are smaller in absolute value compared to the long-run estimates. Further, the estimates are close to being evenly distributed across four beverage-types (i.e. beer, wine, spirits and a composite of these three, labelled alcohol), with wine and spirits being most responsive to price and income, while spirits and alcohol are most responsive to advertising.

There are several differences in the specification of alcohol demand across the literatures that are evident in Table 2. First, although many elasticity estimates come from traditional linear or double-log specifications, recent studies increasingly adopt functional forms (such as the almost ideal demand system (AIDS), the Rotterdam model, or a hybrid of these (two) that are consistent with consumer theory. Indeed, median elasticities tend to be larger in absolute value for estimates based on these newer specifications. Second, studies that account for the addictive nature of alcohol typically model addiction in a myopic manner, whereby lagged values of consumption are included on the right-side of the demand equation. This is different from rational addiction specifications, which allow consumers to be backward- and forward-looking by including lead and lagged consumption in demand. Third, some studies account for smuggling of alcohol across geographical boundaries, whilst others estimate a double hurdle model, whereby the demand for alcohol is related to the decision to drink, as well as the quantity consumed. Fourth, although relatively few studies include the price of tobacco in the specification of alcohol demand (to account for alcohol and tobacco being complements or substitutes), many studies do include the prices of other alcoholic beverages in the demand for a particular beverage.

Concerning data issues, although some studies (e.g. Nelson 2003) account for differences in pure alcohol (ethanol) content across beverages (with beer (spirits) containing the least (most) ethanol per equivalent unit), the most common elasticity estimate comes from a per capita demand model that does not measure quantity in ethanol-equivalent units. Also, although it is most common for the model to be aggregated to the country-level and estimated with time-series data, a small number of price and income elasticity estimates are gender-specific or coincide with specific age groups (i.e. teens are less than 18 years of age, young adults are in the 18–24 age group and adults are older than 24 years of age). Moreover, as indicated in Table 2, across different data constructs, the elasticities vary greatly. For example, the median price elasticity for the product of an alcohol producer (–1.207) is nearly twice the medians of other aggregations; while, at the median, women and adults tend to be more responsive to price than men and young adults.

With respect to estimation methods, price and income elasticities are most commonly constructed from demand models that are estimated using ordinary least squares (OLS), whereas the most common advertising elasticity comes from seemingly unrelated regression (SUR) estimation. Other less-utilised estimation techniques include two stage least squares (2SLS), three stage least squares (3SLS), full information maximum likelihood (FIML), single-equation maximum likelihood (MLE), generalised method of moments (GMM) and generalised least squares (GLS). Table 2 suggests that the elasticities are particularly sensitive to 3SLS and GMM.

Finally, some elasticity estimates come from models that correct the error term for serial correlation or heteroskedasticity, or adjust the data for multi-collinearity (typically using ridge regression procedures), while less than 20 per cent of the price and income elasticities are reported in studies published in the top 36 journals. Moreover, fewer than 5 per cent of the advertising elasticities are published in similar leading journals.

3. Meta-regression procedure

Although a perusal of Table 2 suggests that elasticity estimates are sensitive to modelling characteristics, since the medians do not control for multiple factors influencing the elasticities, the extent to which modelling procedures matter remains in question. Accordingly, similar to other meta-analyses (e.g. Smith and Huang 1995; Espey 1998; Stanley 1998; Espey and Thilmany 2000; List and Gallet 2001; Gallet and List 2003), we estimate meta-regressions for the price, income and advertising elasticities of alcohol. This involves regressing the elasticity estimates on variables that account for study attributes. In particular, a series of dichotomous variables is used to account for the characteristics listed in Table 2 (i.e. the variable equals one if a particular characteristic applies, zero if not).

Although Fogarty (2004) adopts a similar approach in his study of alcohol demand, this study differs in three key respects. First, Fogarty includes 150 elasticity estimates from 64 studies published prior to 1994, whereas our sample includes more studies and more elasticity estimates. Second, Fogarty focuses on the price elasticity, whereas our study addresses the determinants of the price, income and advertising elasticities. Third, similar to other meta-analyses (e.g. Espey 1998; Gallet and List 2003), which account for specification, data and estimation attributes of studies, we include more attributes in our meta-regressions than does Fogarty.

Before estimating the meta-regression model, several issues need to be addressed. First, results are always interpreted relative to the baseline (i.e. all dichotomous variables set equal to zero); and for several characteristics (e.g. functional form and estimation method), since the list of characteristics encompasses all observations, one of the dichotomous variables is omitted to serve as the baseline. Accordingly, the baseline for the price elasticity model corresponds to a long-run elasticity estimate of the total quantity of beer demanded (not in ethanol-equivalent units), which does not account for addiction, smuggling or two-part decisions involving the choice to drink and the quantity consumed. Also, the baseline model does not include tobacco and other alcohol prices in the specification of demand (which is estimated using OLS with gender- and age-neutral cross-sectional data at the state/province level). Lastly, the baseline model does not account for error corrections or multicollinearity and is based on work that is not published in a top 36 journal. Setting the dichotomous variables equal to zero results in somewhat similar baselines for the income and advertising elasticities.

Second, a positive (negative) coefficient means the respective study attribute leads to a higher (lower) value of the elasticity; and so, given the income and advertising (price) elasticities are typically positive (negative), this implies that a positive coefficient yields a more elastic (inelastic) income and advertising (price) elasticity. The opposite holds for a negative coefficient.

Third, an issue commonly encountered in meta-analysis is the lack of independence across observations of the dependent variable. For example, as indicated in Table 1, since several authors have written multiple studies on the demand for alcohol, if similar procedures are used from one study to the next, this may lead to correlation in the estimated elasticities across studies. To address this issue, we adopt a procedure similar to Espey (1998) and Espey and Thilmany (2000). Namely, we create a series of dummy variables, one for each specific author (e.g. Duffy) or set of authors (e.g. Baltagi and Griffin) who have written multiple studies listed in Table 1 (i.e. the variable equals one if the elasticity is from a study authored by someone who has written other studies listed in Table 1, zero otherwise). For each elasticity, therefore, depending on whether a particular author has estimated the elasticity across multiple studies, we include up to 21 additional author-specific dummy variables in the meta-regression. In light of the volume of author-specific dummy variables, however, we do not report the estimated coefficients of each of these variables. Rather, at the bottom of Table 3 we report the *F*-test values to assess the joint significance of the author-specific coefficients.

Table 3 Meta-regression estimation results†

		Elasticity		
Category	Variable	*Price*	*Income*	*Advertising*
Elasticity estimate:	Short-run	0.32*	–0.31**	0.01
		(1.69)	(2.21)	(0.09)
Beverage:	Wine	–0.28***	0.71***	0.02
		(3.29)	(9.88)	(0.66)
	Spirits	–0.26***	0.38***	0.08***
		(2.82)	(4.36)	(3.52)
	Alcohol	–0.26***	0.20**	–0.01
		(2.76)	(2.53)	(0.36)
Specification:	Functional form:			
	Double-log	0.25	0.14	–0.22***
		(1.49)	(1.44)	(2.68)
	Semi-log	0.48**	0.51***	–0.23***
		(2.24)	(3.33)	(2.78)
	AIDS	0.55**	–0.14	–0.06
		(2.21)	(0.90)	(0.58)
	Rotterdam	0.80***	–0.13	–0.07
		(3.33)	(0.90)	(0.70)
	Hybrid	0.66***	–0.09	–0.07
		(2.91)	(0.49)	(0.68)
	Addiction:			
	Myopic	0.06	–0.50***	–0.19
		(0.4)	(5.47)	(1.46)
	Rational	–0.03	–	–
		(0.11)		
	Other issues:			
	Smuggling	0.12	–0.04	–
		(0.59)	(0.31)	
	Hurdle	–0.17	0.04	–
		(0.60)	(0.20)	
	Tobacco price	0.38**	0.16	–0.07
		(2.41)	(1.48)	(0.82)
	Other alcohol price	–0.37***	0.29***	–0.07*
		(2.83)	(2.83)	(1.87)
Data:	Quantity:			
	Per capita	0.44**	–0.31**	–0.14
		(1.99)	(1.98)	(1.30)
	Ethanol-equivalent	0.04	–0.14	–0.47***
		(0.30)	(1.26)	(2.69)
	Time series	0.02	–0.05	–
		(0.14)	(0.32)	
	Panel	0.15	–0.39***	–
		(0.96)	(2.73)	
	Aggregation:			
	Country	0.28*	–0.18	0.56**
		(1.85)	(1.44)	(2.48)
	Individual	0.02	–0.56***	–
		(0.06)	(3.16)	
	Firm	0.61	–	–
		(1.50)		
	Gender:			
	Men	0.72	–0.27	–
		(1.40)	(0.69)	
	Women	0.48	–0.05	–
		(0.93)	(0.18)	

Table 3 *Continued*

Category	Variable	Elasticity		
		Price	*Income*	*Advertising*
	Age:			
	Adult	0.69*	−0.06	–
		(1.94)	(0.21)	
	Young adult	1.32***	−0.16	–
		(3.34)	(0.38)	
	Teen	2.81***	−1.04***	–
		(12.11)	(5.09)	
Estimation:	Method:			
	2SLS	−0.54**	0.42**	0.12***
		(2.20)	(2.18)	(4.31)
	3SLS	−0.38**	0.05	0.05*
		(2.56)	(0.38)	(1.72)
	FIML	0.02	0.38**	−0.12
		(0.15)	(2.29)	(0.82)
	MLE	0.19*	−0.14	0.04
		(1.82)	(1.52	−1.61
	SUR	0.02	0.03	(0.08
		(0.13)	(0.31)	−1.16
	GMM	0.61	–	–
		(0.23)		
	GLS	0.15	−0.30***	−0.45**
		(1.09)	(3.26)	(2.37)
	Corrections:			
	Serial correlation	−0.03	0.11	0.13**
		(0.14)	(0.83)	(2)
	Heteroskedasticity	0.17	0.04	0.06
		(0.76)	(0.22)	(0.59)
	Multicollinearity	0.52**	−0.11	–
		(2.47)	(0.70)	
Publication:	Date of publication	−0.02*	0.01*	−0.01***
		(1.76)	(1.67)	(2.75)
	Top 36 journal	−0.55**	0.37**	0.03
		(2.07)	(2.53)	(0.78)
Constant		29.17*	−15.41	15.15***
		(1.69)	(1.55)	(2.79)
F(Beverage)‡		4.51	33.41	5.8
F(Specification)		1.94	6.04	2.92
F(Data)		2.17	1.78	3.26
F(Estimation)		1.96	2.76	3.6
F(Publication)		9.04	5.25	1.63
F(Country)		1.38	2.12	1.99
F(Author)		2.97	3.77	1.2
R^2		0.17	0.35	0.35
Sample size		1172	1014	322

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.
†*t*-statistics in absolute value in parentheses below coefficient estimates. To conserve space, estimated coefficients of country-specific and author-specific dummy variables are not included in the table.
‡*F*-tests of the joint significance of coefficients associated with respective categories. For example, *F*(Beverage) refers to an *F*-test of the significance of the three coefficients of the beverage dummy variables, while *F*(Country) and *F*(Author) assess the joint significance of the coefficients associated with the country-specific and author-specific dummy variables, respectively.

Fourth, in addition to the variables corresponding to Table 2, as well as the author-specific dummy variables, other variables were included to account for two additional issues. In particular, since later studies build off the results of earlier studies, we include the year of publication as a regressor. This variable accounts for general changes in modelling procedures over time that are not accounted for by the attributes provided in Table 2. Also, since the 132 studies estimate alcohol demand across 24 countries (i.e. Austria, Australia, Belgium, Canada, China, Cyprus, Denmark, Finland, France, Germany, Greece, India, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Poland, Portugal, Spain, Sweden, United States and the United Kingdom), to account for country-specific characteristics we include dummy variables for the different countries in the model. To conserve space, though, similar to the author-specific variables, we do not report the estimated coefficients of the country-specific dummy variables, choosing instead to report *F*-test values of their joint significance.

Fifth, characteristics for which elasticity estimates do not exist are not included in the meta-regression. For example, since there are no income and advertising elasticities estimated from rational addiction models, a dichotomous variable corresponding to rational addiction is not included in the income and advertising elasticity regressions.

Sixth, tests revealed the presence of heteroskedasticity of the error term in each meta-regression. Therefore, for each meta-regression, White's (1980) correction procedure was used to adjust the standard errors.

4. Estimation results

Table 3 contains the parameter estimates for the price, income and advertising elasticity regressions. Before discussing the importance of individual characteristics, *F*-tests of the joint significance of the regressors in each major category were performed. As provided at the bottom of Table 3, for the price and income elasticity models, the estimated coefficients of the variables in each of the major categories listed in Table 2, as well as the country-specific and author-specific categories, are jointly significant at conventional levels. However, for the advertising elasticity model significance is more sparse, as we find it lacking for the publication and author categories. Accordingly, the role of modelling procedures as determinants of the elasticity estimates differs across the three elasticities. Results for each elasticity are discussed separately below.

4.1 Price elasticity

As evidenced in Table 3, many of the estimated coefficients of the price elasticity meta-regression are significantly different from zero. Consider the results for the short-run price elasticity. Given the long-run price elasticity serves as the baseline, the positive coefficient of the short-run variable supports the conventional wisdom that short-run elasticity estimates are more inelastic than long-run elasticity estimates. Also, given that the price elasticity of beer serves as the baseline, the negative coefficients of the other three beverage-category variables imply that the demand for beer is more price inelastic than the other beverage-types, which is consistent with many other studies (e.g. Johnson and Oksanen 1977; Clements and Johnson 1983; Thom 1984; Duffy 1987; Nelson and Moran 1995). Interestingly, to allow comparisons across all four beverages, regressions were also performed with different beverages serving as the baseline. Although the price elasticity for beer remained significantly different from all other beverages, we found no statistical difference between the price elasticities of wine, spirits and alcohol.

Focusing on those coefficients that are significantly different from zero, there are several meaningful results associated with the remaining categories. First, compared to a linear model of beer demand, other functional forms tend to provide more inelastic estimates of the price elasticity. Second, the price elasticity tends to be more inelastic when the price of tobacco (price of other alcohol) is (is not) included as a determinant of per capita country-level consumption. Third, since the coefficients associated with the age variables are positive and larger with younger age groups, this suggests that younger individuals are less responsive to price than older individuals; which is odd, in light of studies of other addictive goods (namely cigarettes) that find younger individuals are more responsive to price partly because they have been less exposed to the addictive good (see Lewit *et al*. 1981). In the case of alcohol, though, such counter-intuitive results could be tied to differences in the consumption bundle across age groups, such that if older individuals consume a greater share of more price sensitive beverages (i.e. wine and spirits) then we may find the price elasticity of alcohol for older individuals is more elastic. Fourth, relative to OLS, price elasticity estimates tend to be more (less) elastic when 2SLS and 3SLS (MLE) are used as the estimation method, without correction for multicollinearity. Fifth, the 'culture of the profession' has a noticeable impact on the price elasticity estimates, as more recent studies that are published in top 36 journals tend to report more elastic estimates. Hence, perhaps earlier studies, coupled with the review process of top journals, shapes the direction of future research.

Yet with many of the coefficients being insignificant for a variety of attributes, including accounting for addiction, smuggling, double-hurdle modelling of demand, ethanol-equivalent units, whether the data is time-series, cross-sectional, or panel (and individual-level or firm-level), gender differences, as well as many of the estimation methods and corrections, such attributes fail to have much impact on the estimated price elasticities.

4.2 Income elasticity

The income elasticity results, which are also provided in Table 3, indicate several tendencies. For instance, given the median income elasticity is positive and that the coefficient of the short-run variable is significantly negative, this implies that short-run income elasticity estimates tend to be more inelastic than long-run estimates. Also, consistent with other studies (e.g. Johnson 1985; Selvanathan 1991; Nelson and Moran 1995), the income elasticity is larger for wine, spirits and alcohol. Furthermore, changing the baseline to allow for comparisons between all beverages, we find significant differences in the income elasticity across beer, wine and spirits, with wine having the largest income elasticity, followed by spirits and then beer.

Focusing on the remaining coefficients that are significant, we find the semilog functional form inflates the income elasticity estimates. Also, including other alcohol prices in the demand equation, estimating demand with 2SLS or FIML, and publishing the results in a more recent top 36 journal further increase the income elasticity. Yet a variety of factors (i.e. accounting for myopic addiction, using per capita (and individual-level) panel data, focusing on teens and estimating demand with GLS) dampen the income elasticity estimates. Nonetheless, it is important to note that many factors (i.e. most functional forms, smuggling, double hurdle models, inclusion of tobacco price, ethanol-equivalent units, time-series country-level data, gender, older age groups, and a variety of estimation methods and corrections) do not appreciably influence the income elasticity.

4.3 Advertising elasticity

Because of the paucity of advertising elasticity estimates in the literature, there are fewer differences across studies. Although this resulted in many characteristics being dropped from the advertising elasticity meta-regression, the results presented in the last column of Table 3 do indicate that many of the remaining characteristics influence the advertising elasticity estimates. For instance, given the advertising elasticity tends to be positive, the demand for spirits is more responsive to advertising than the demand for beer. Indeed, changing the baseline to other beverages, we find the advertising elasticity to be larger for spirits compared to all other beverages. However, there are no statistical differences between the advertising elasticities of beer, wine and alcohol. Also, the advertising elasticity tends to be smaller for more recent studies, with a double-log or semilog specification, which includes other alcohol prices, measures quantity in ethanol-equivalent units, and is estimated using GLS. Yet the advertising elasticity tends to be larger when demand is estimated with country-level data (using 2SLS or 3SLS) and corrected for serial correlation. But again, similar to the other elasticities, the coefficients of many of the study attributes (such as controlling for the short-run or long-run, several functional forms, addiction, tobacco price, per capita consumption, several estimation issues and quality of journal) are insignificant and so do not contribute to differences in advertising elasticity estimates across studies.

5. Conclusion

Surveying 132 studies of alcohol demand, the results of our meta-analysis are useful in a number of respects. First, since we find elasticity estimates are sensitive to a variety of factors, we gain a better understanding of the nuances of alcohol demand. For example, with respect to the price elasticity, Table 2 indicates that the most common study attributes correspond to a short-run country-wide per capita demand for beer, which is based on a double-log specification and estimated with time-series data using OLS. Evaluated at the median year of publication (1992), the results for the price elasticity meta-regression predict the price elasticity of beer corresponding to such attributes equals –0.83. Accordingly, for similar study attributes, we predict price elasticity estimates for wine and spirits to be –1.11 (i.e. – (0.83 + 0.28)) and –1.09 (i.e. – (0.83 + 0.26)), respectively. Such estimates are well within one standard deviation of the mean for the literature as a whole, and are also consistent with beer being more price inelastic compared to wine and spirits.

Second, our results highlight the importance of accounting for different attributes of alcohol demand when designing policies. Consider, for example, the case of alcohol taxes. Given that we find differences in the price elasticity across beverages and consumer age groups, the optimal tax on alcohol should account for such differences. Also, since all three elasticities are sensitive to the inclusion of other alcohol prices in the demand equation, the optimal tax will likely need to account for interdependencies in demand across alcohol beverages. Moreover, if we are particularly concerned with teenage drinking, since we find that teens are least responsive to price, then perhaps the best approach to reducing teen alcohol consumption should involve alternatives to taxation, such as education campaigns. As for policies directed towards advertising (e.g. advertising bans), since the demand for spirits is most responsive to advertising, limits on advertising will be most effective at reducing alcohol consumption if they are directed towards media most often used by distillers.

Lastly, several of the estimated coefficients in our meta-regressions are insignificantly different from zero, which provides further information to those interested in alcohol demand issues. In particular, there are many insignificant coefficients for the variables related to the nature of the data (be it time-series, cross-sectional or panel), several estimation methods and corrections, and a few other issues, such as whether or not demand accounts for addiction, smuggling and gender differences. Consequently, with elasticity estimates being somewhat insulated from these attributes, this should draw less concern when choosing an elasticity estimate to base policy prescriptions.

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