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ADDICTION

Cigarette demand: a meta-analysis of elasticities

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Summary

Estimating elasticities of cigarette demand has become commonplace amongst economists and policymakers. Synthesizing the various elasticities into a coherent message is quite challenging, however, as the point estimates are obtained using quite disparate modeling techniques and data. In this study, we perform a meta-analysis to explore factors that influence variations within and across studies. Empirical results suggest that demand specification, data issues, and estimation methodology have varying degrees of influence on reported estimates of price, income, and advertising elasticities. Copyright © 2002 John Wiley & Sons, Ltd.

Keywords cigarette demand elasticities; meta-analysis

Introduction

Given the volume of information on the health risks of cigarette smoking, in the interest of public health, governments have used instruments ranging from taxation to restrictions on the marketing of cigarettes to reduce the incidence of smoking. Since the efficacy of different policy instruments depends upon the nature of cigarette demand, understanding the structure of the demand relationship is important. For example, from the standpoint of taxation, whether the underlying goal is to enhance public health or raise revenue, the impact of cigarette taxes on consumption is necessarily tied to the price elasticity of demand. Hence, numerous studies have estimated cigarette demand elasticities using a variety of data and techniques.

Although individual studies of cigarette demand continue to garner attention in the literature, given disparities in the elasticity estimates, it is challenging to summarize the results to date. Indeed, recent literature reviews [1,2] suggest that elasticity estimates are sensitive to a variety of modeling techniques. With this in mind, this paper complements the extant literature by statistically analyzing the characteristics of cigarette studies to uncover key factors that affect the estimated price, income, and advertising elasticities of cigarette demand. Utilizing meta-analysis techniques, we examine the sensitivity of elasticity estimates to a variety of modeling approaches, which include amongst other things functional form, estimation technique, and data issues.

This study is similar in spirit to other meta-analyses, which have provided insights into such diverse topics as the valuation of environmental amenities [3,4], Ricardian equivalence [5], and gasoline demand [6]. In our empirical model, amongst other issues, we address the following questions: (1) Are short-run and long-run elasticity estimates similar? (2) Does functional form influence the estimated elasticities? (3) Do models that account for such factors as addiction or smuggling

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yield heterogeneous elasticity estimates? (4) Are elasticity estimates sensitive to data constructs (e.g. degree of aggregation, gender- or age-specific data, and time span covered)? (5) Do estimation procedures, such as two-stage least squares or generalized method of moments, affect elasticity estimates? (6) Do adjustments to the data, such as error correction (e.g. serial correlation or heteroskedasticity) influence the estimated elasticities? And (7), given that current studies rest upon the shoulders of earlier studies, are elasticity estimates sensitive to time or the quality of the publication outlet?

The paper proceeds as follows. The next section discusses the merits of meta-analysis. This is followed by a discussion of the data collected from the cigarette literature. The empirical model and estimation results are then presented. The paper concludes with a summary of the findings.

Merits of meta-analysis

When conducting a meta-analysis, the researcher attempts to uncover the sensitivity of a particular parameter estimate, such as an elasticity, to the variety of design methods used in the existing body of literature. In particular, by treating the parameter of interest as the dependent variable, through the use of dichotomous variables (i.e. set equal to one if a particular technique is used, zero if not) the researcher can assess the quantitative importance of different techniques on the parameter. In this sense, meta-analysis is a statistical 'analysis of analyses'.

Unlike qualitative literature reviews, however, by quantifying the importance of design methods, recent reviews [7–9] discuss several benefits of meta-analysis over traditional literature reviews. First, traditional literature reviews may be misdirected by the subjective decision of the reviewer to exclude certain studies deemed 'inappropriate' or to emphasize certain study attributes over others. In the case of meta-analysis, however, subjective impressions are replaced by statistical tests, such that the data determine the importance of modeling procedures. Second, although individual studies may provide conflicting results, by pooling all of the results into a single meta-regression, this cannot only help to clarify general tendencies in the literature, but it can also increase the power of statistical tests. Third, by uncovering the statistical importance, or lack of importance, of particular design methods, new avenues of research can be suggested by the results. For example, if an estimated parameter is significantly different across various regimes, this suggests further research to uncover the theoretical or empirical reasons for such results.

Although meta-analysis can shed light on various nuances in the literature, similar to traditional literature reviews it is not without limitations. For example, as elaborated by Stanley [8] and others, if specification errors are consistently adopted in the literature, then the meta-regression will fail to account for these errors. Also, since the researcher must specify which design attributes to include in the meta-regression, disagreements may emerge on the chosen set of explanatory variables. Hence, rather than view meta-analysis as a cure for all empirical ills, it is best to view it as an objective method for analyzing statistical patterns in current modeling procedures.

Data

Several steps were taken to compile the literature for this study. First, a search of available literature was performed using *EconLit*. This resulted in a substantial listing of published and unpublished works. Second, existing qualitative literature reviews, such as Chaloupka and Warner's [2] chapter in the *Handbook of Health Economics*, were consulted for possible studies not listed in *EconLit*. Third, the reference sections of all studies obtained in steps (1) and (2) were checked for any additional studies. In the end, 86 different studies were retrieved that reported point estimates of the price, income, and/or advertising elasticities of demand. These studies are presented in Table 1.

Due to the refinement of econometric techniques and the growing availability of data, it is not surprising to find significant differences in elasticity estimates across studies. For instance, while the mean price elasticity across the 86 studies is −0.48, suggesting that cigarette demand is generally inelastic, the standard deviation is quite large (0.43), as is the range of estimates (−3.12 to 1.41). Coupling these results with the fact that advertising and income elasticities display similar variation (i.e. the mean income elasticity is 0.42, with a standard deviation (range) equal to 0.49 (−0.80 to 3.03); while the mean advertising elasticity is 0.10, with a standard deviation (range)

Table 1. Studies included in the Meta-Analysis[a]

Author(s)	Year published	Author(s)	Year published
Abernathy and Teel	1986	Koutsoyannis	1963
Atkinson and Skegg	1973	Lanoie and Leclair	1998
Baltagi and Levin	1986	Laugesen and Meads	1991
Bardsley and Olekalns	1998	Leeflang and Meads	1985
Barnett, Keeler, and Hu	1995	Leu	1984
Bass	1969	Lewit, Coate, and Grossman	1981
Becker, Grossman, and Murphy	1991	Lewit and Coate	1982
Bishop and Yoo	1986	Maier	1955
Blaine and Reed	1994	McAuliffe	1988
Boyd and Seldon	1990	McGuinness and Cowling	1975
Chaloupka	1991	McLeod	1986
Chaloupka	1992	Pekurinen	1989
Chaloupka and Grossman	1996	Peto	1974
Chaloupka and Saffer	1992	Porter	1986
Chaloupka and Wechsler	1997	Prest	1949
Chapman and Richardson	1990	Radfar	1985
Chetwynd, Coope, Brodie, and Wells	1988	Reekie	1994
Cox and Smith	1984	Russell	1973
Dominguez and Page	1971	Sackrin	1957
Duffy	1991	Sackrin	1962
Duffy	1995	Saffer and Chaloupka	1999
Evans and Farrelly	1998	Schmalensee	1972
Evans, Ringel, and Stech	1999	Schnabel	1972
Farr, Tremblay, and Tremblay	2001	Schneider, Klein, and Murphy	1981
Farrelly and Bray	1998	Schoenberg	1933
Franke	1994	Seldon and Boyd	1991
Fujii	1980	Seldon and Doroodian	1989
Gallet	1999	Simonich	1991
Galbraith and Kaiserman	1997	Stravinos	1987
Goel and Morey	1995	Stone	1945
Hadan	1990	Sumner	1971
Hamilton	1972	Sung, Hu, and Keeler	1994
Harris and Chan	1999	Tansel	1993
Holak and Reedy	1986	Tegene	1991
Hsieh, Hu, and Lin	1999	Townsend	1987
Hu, Sung, and Keeler	1995	Tremblay and Tremblay	1995
Ippolito, Murphy, and Sant	1979	Valdes	1993
Jackson and Saba	1997	Vernon, Rives, and Naylor	1969
Johnson	1986	Warner	1981
Jones	1989	Wasserman, Manning, Newhouse, and Winkler	1991
Jones and Posnett	1988	Witt and Pass	1981
Kao and Tremblay	1988	Young	1983
Keeler, Hu, Barnett, and Manning	1993	Yurikeli and Zhang	2000

[a] In an effort to conserve space, only those studies that are cited in the body of the paper are included in the reference section. A complete list of references, including those in Table 1, is available from the authors upon request.

equal to 0.13 (−0.10 to 0.69)), the difficulty of properly synthesizing these results becomes readily apparent.

When gathering information from the 86 empirical studies, our goal was to estimate the sensitivity of point elasticity estimates to variables that were common to a majority of studies. Similar to Espey [6], we obtained information on several broad categories, including the type of elasticity estimate, demand specification, data, and estimation procedure. Furthermore, given that studies are often motivated by prior work, we also account for the sensitivity of the elasticity estimates to characteristics of the publication, namely the date of publication and whether or not the study appeared in a higher-rated economics journal.[a] Table 2 presents the frequencies and median elasticity values across the selected variables from the 86 studies.

Table 2. Frequency of variables included in the elasticity equation

Category	Variable	Number of observations (median elasticity)[a]		
		Price	Income	Advertising
Elasticity estimate	Short-run	368 (−0.40)	295 (0.28)	96 (0.07)
	Long-run	155 (−0.44)	80 (0.39)	41 (0.09)
Demand specification	Functional form			
	Linear	231 (−0.45)	69 (0.23)	13 (0.03)
	Double-log	284 (−0.37)	304 (0.34)	123 (0.08)
	Semi-log	8 (−0.41)	2 (0.18)	1 (0.10)
	Addiction			
	Myopic	155 (−0.38)	163 (0.25)	82 (0.10)
	Rational	122 (−0.44)	5 (0.06)	0
	Other	0	0	6 (0.03)
	Other issues			
	Cig/alcohol demand system	16 (−0.37)	12 (0.99)	6 (−0.01)
	Almost ideal demand system	15 (−0.38)	11 (1.01)	0
	Smuggling	66 (−0.36)	16 (0.03)	0
	Hurdle	30 (−0.85)	3 (0.15)	0
Data	Quantity			
	Cigarettes	405 (−0.44)	266 (0.24)	119 (0.08)
	Tobacco	118 (−0.35)	109 (0.49)	18 (0.06)
	Total	155 (−0.45)	72 (0.41)	19 (0.09)
	Per capita	368 (−0.41)	303 (0.29)	118 (0.07)
	Time-series	329 (−0.41)	328 (0.34)	137 (0.08)
	Cross-sectional	90 (−0.42)	19 (0.10)	0
	Cross-sectional-time-series	104 (−0.43)	28 (0.09)	0
	Aggregation			
	Country	335 (−0.40)	341 (0.33)	137 (0.08)
	State/province	101 (−0.60)	24 (0.30)	0
	Individual	87 (−0.39)	10 (0.06)	0
	Gender			
	Men	24 (−0.50)	11 (0.27)	0
	Women	15 (−0.34)	8 (1.23)	0
	Age			
	Adult	17 (−0.32)	6 (0.06)	0
	Teen	8 (−1.43)	0	0
	Young adult	22 (−0.76)	1 (0.05)	0
	Time period			
	Pre-1964	29 (−0.42)	37 (0.34)	0
	Post-1964	147 (−0.40)	42 (0.17)	0

Table 2 (*continued*)

Category	Variable	Number of observations (median elasticity)[a]		
		Price	Income	Advertising
Estimation	Method			
	OLS	295 (−0.40)	262 (0.33)	69 (0.05)
	2SLS	173 (−0.44)	78 (0.24)	47 (0.10)
	3SLS	15 (−0.43)	15 (0.44)	3 (0.08)
	FIML	6 (−0.41)	0	0
	MLE	19 (−0.32)	17 (0.24)	18 (0.15)
	SUR	3 (−0.95)	3 (0.16)	0
	GMM	5 (−0.74)	0	0
	GLS	7 (−0.33)	0	0
	Corrections			
	Serial correlation			
	AR	35 (−0.47)	25 (0.64)	17 (0.09)
	MA	5 (−0.25)	2 (−0.13)	0
	Heteroskedasticity	10 (−0.47)	0	0
	Multicollinearity	17 (−0.69)	12 (0.32)	20 (0.04)
Publication	Top 36 Journals	156 (−0.47)	61 (0.74)	43 (0.09)
Total observation		523	375	137

[a] Figures for the median elasticities correspond to the median across all elasticities reported for a particular variable. For example, across the 368 short run price elasticity estimates, the median value is –0.40.

Our scouring of the literature yielded 523 estimated price elasticities, 375 estimated income elasticities, and 137 estimated advertising elasticities. With respect to the price elasticity, Table 2 indicates that there are several differences in demand specification across the literature. First, of the 523 estimated price elasticities (368 short-run estimates and 155 long-run estimates), 231 are derived from a linear demand specification, 284 from a double-log specification, and 8 from a semi-log specification. Second, slightly more than 50% of the price elasticity estimates are from models that account for addiction (277), with the majority of these estimates from myopic addiction models (155) as opposed to rational addiction models (122).[b] Third, relatively few estimates are from models that estimate price elasticity from a system of cigarette and alcohol demand equations (16) or via an almost ideal demand system (15). Fourth, several studies account for smuggling/bootlegging (66) in the demand specification or use a double-hurdle approach (30), whereby the demand for cigarettes is linked to the decision to smoke, as well as the quantity smoked (see Jones [12]).[c]

Concerning differences in the data across the 523 price elasticity estimates, we find that most studies measure quantity in per capita terms (368) rather than total (155), with consumption most often referring to cigarettes (405) as opposed to units (e.g. pounds) of tobacco (118). Also, the majority of price elasticity estimates are from studies that use time-series data (329) aggregated to the country-level (335), versus less-aggregated data (i.e. at the state/province (101) or individual consumer (87) levels). Finally, a small number of price elasticity estimates are from studies that specifically examine gender or age groups (i.e. teen (age less than 18), young adult (age 18-24), or adult (age greater than 24)); likewise, few studies use data restricted to the pre- or post-1964 periods (coinciding with the 1964 Surgeon General's Report).[d]

In terms of model estimation, most price elasticities (295) are from demand equations estimated using ordinary least squares (OLS), as opposed to two stage least squares (2SLS), three stage least squares (3SLS), full-information maximum likelihood (FIML), single-equation maximum likelihood (MLE), seemingly unrelated regressions (SUR), generalized method of moments (GMM), or generalized least squares (GLS). Moreover, in addition to adjusting the error structure of the model by accounting for serial correlation (using an autoregressive (35) or moving average (5) process) or heteroskedasticity (10), some studies do take account of multicollinearity (17) in the model (typically using ridge regression techniques). Lastly, of the 523 price elasticity estimates, 156 are from studies published in a journal appearing in the Scott and Mitias [10] list of the top 36 economics journals.

In addition to the frequencies of the variables associated with the income and advertising elasticities, Table 2 also suggests a great deal of variability in the elasticity estimates across the various categories. For example, with respect to the price elasticity, the median elasticity estimate (-1.43) for those studies specific to teen cigarette demand is largest (in absolute value), as compared to all other categories; whereas the smallest (in absolute value) median elasticity estimate (-0.25) is associated with those studies that correct for serial correlation of the error term using a moving average transformation. Nonetheless, since these median figures do not control for other facets of modeling procedures, the extent to which the elasticities are sensitive to the various model attributes remains in question.

Empirical model

When statistically examining the data, previous meta-analyses typically pool the data, and thereby ignore the dependence of observations across and within studies. This particular feature of the literature is unfortunate, as biased and inconsistent parameter estimates may result if the panel characteristic of the data is not accounted for in the estimation equation. Accordingly, given that the typical study cited in Table 1 provides numerous elasticity estimates, we begin by treating the data as panel in nature and therefore estimate versions of the following unbalanced panel data model:

$$E_{ij} = \alpha_i + \beta X_{ij} + e_{ij} \qquad (1)$$

where E_{ij} denotes study i's jth elasticity estimate; α_i represents a 'random researcher' effect, which controls for individual specific effects that may impact reported elasticity estimates. The random effects provide a control for the commonality within a study, and control for the dependence of observations within and across each paper. β are estimated response coefficients; X_{ij} are factors presumed to affect the reported elasticity. In X_{ij}, provided the rank condition is satisfied, we include the set of regressors in Table 2 as a series of dummy variables set equal to 1 if the modeling technique is used and 0 otherwise. In some cases, particularly with respect to the advertising elasticity, due to the paucity of data we exclude certain regressors because the rank condition is not satisfied.[e] Furthermore, in addition to the variables in Table 2, to account for possible drift of the elasticity estimates over time, we include in X_{ij} the publication date of the study. Lastly, e_{ij} are iid error terms with a zero mean and constant variance σ_e^2.

Before discussing the empirical estimates of Equation (1), a few aspects of the estimation procedure are worth mentioning. First, given that we treat unmeasured characteristics α_i as error components, generalized least squares estimation of Equation (1) economizes on degrees of freedom, yields coefficients that are not conditioned on unmeasured researcher effects, and draws the α_i from a Gaussian distribution. An alternative procedure is to treat α_i as parametric shifts of the regression equation. This technique is commonly termed a fixed effects or covariance model, whereby estimates of the marginal effects are conditioned on the unmeasured characteristics. We use a random effects approach due to its increased efficiency, and because many of the estimates within each study are obtained from one regression model, leaving no variation in X_{ij}—without variation in X_{ij} our hypotheses are untestable since any static regressors are perfectly correlated with the fixed effects, compromising the rank condition.

Second, in addition to the unbalanced panel estimates, we report empirical results from two alternative models, namely ordinary least squares (OLS) and a group means regression. The former model potentially yields biased and inconsistent estimates if omitted variables captured by the researcher effects are correlated with the regressor vector. If the orthogonality assumption is met, OLS estimates are inefficient if unobservables induce the error terms in Equation (1) to be correlated across published results for a particular researcher. The latter model expresses the data in 'researcher' means (e.g. E_{ij} (X_{ij}) is replaced with

$E_i = J^{-1} \sum_j E_{ij}(X_i = J^{-1} \sum_j X_{ij})$); and, as such, this particular regression model is considered a between estimator because the β are estimated based on only cross-study variation. While the group means regression model is analogous to a typical cross-sectional estimation procedure, within a panel data context this specification is usually inefficient since important information is lost in the aggregation process.[f]

Estimation results

Tables 3–5 contain the estimation results using price, income, and advertising elasticities as the regressands. Each table contains the three distinct model types as discussed above. In the case of the random effects model, as applied to the price and income elasticity equations, statistical tests of the homogeneity of the individual effects leads us

Table 3. Empirical estimates for the price elasticity[a]

Category	Variable	Model type		
		OLS	Random	Group means
Elasticity estimate	Short-run	0.14	0.13	0.55
		(2.77)	(5.91)	(1.57)
Demand specification	Functional form			
	Linear	0.20	0.14	0.57
		(1.34)	(0.63)	(1.87)
	Double-log	0.24	0.10	0.64
		(1.65)	(0.43)	(2.04)
	Addiction			
	Myopic	−0.09	−0.03	0.14
		(1.39)	(0.55)	(0.69)
	Rational	0.50	0.06	0.81
		(4.41)	(0.50)	(2.91)
	Other	—	—	—
	Other issues			
	Cigarette/alcohol demand system	0.76	0.63	0.78
		(3.68)	(1.66)	(2.38)
	Almost ideal demand system	−0.68	−0.85	−0.67
		(2.68)	(1.79)	(1.69)
	Smuggling	−0.09	0.29	−0.31
		(1.32)	(5.19)	(2.38)
	Hurdle	−0.24	−0.27	−0.12
		(1.61)	(1.44)	(0.45)
Data	Quantity			
	Tobacco	0.13	0.16	0.10
		(2.45)	(4.92)	(0.91)
	Per capita	0.16	−0.09	0.14
		(2.68)	(1.05)	(1.34)
	Time-series	0.02	0.21	−0.02
		(0.15)	(0.89)	(0.08)
	Cross-sectional	−0.02	−0.03	0.32
		(0.14)	(0.13)	(1.02)
	Aggregation			
	Country	0.40	0.40	0.66
		(2.88)	(0.16)	(2.74)
	Individual	0.57	0.17	0.42
		(2.65)	(0.64)	(0.90)
	Gender			
	Men	−0.04	−0.07	0.01
		(0.43)	(1.35)	(0.07)
	Women	0.37	0.34	0.69

Table 3 (*continued*)

Category	Variable	OLS	Random	Group means
		(3.54)	(6.63)	(1.58)
	Age			
	Adult	0.15	0.18	0.90
		(1.28)	(3.14)	(1.63)
	Teen	−0.64	−0.52	−0.65
		(3.54)	(3.40)	(1.38)
	Young adult	−0.12	0.04	−0.26
		(0.96)	(0.57)	(0.62)
	Time period			
	Pre-1964	0.18	−0.01	0.23
		(1.96)	(0.08)	(1.53)
	Post-1964	0.08	−0.02	0.08
		(0.97)	(0.13)	(0.61)
Estimation	Method			
	2SLS	−0.10	−0.04	−0.05
		(1.62)	(0.87)	(0.32)
	3SLS	0.18	0.07	0.25
		(1.45)	(0.57)	(1.05)
	FIML	0.48	0.42	0.83
		(1.57)	(0.80)	(1.61)
	MLE	0.18	−0.02	0.15
		(1.81)	(0.09)	(0.95)
	SUR	−0.03	0.04	0.04
		(0.09)	(0.07)	(0.08)
	GMM	−0.70	−0.20	−0.52
		(3.09)	(0.47)	(1.25)
	GLS	0.37	0.15	0.62
		(2.19)	(0.57)	(2.25)
	Corrections			
	Serial correlation			
	AR	−0.01	0.07	−0.45
		(0.02)	(1.75)	(1.31)
	MA	0.16	0.05	0.66
		(0.95)	(0.56)	(1.41)
	Heteroskedasticity	0.09	−0.31	0.62
		(0.40)	(1.02)	(1.25)
	Multicollinearity	−0.07	−0.12	−0.12
		(0.54)	(0.48)	(0.59)
Publication	Date of publication	0.01	0.01	0.01
		(2.97)	(1.36)	(2.02)
	Top 36 Journals	−0.14	−0.21	−0.01
		(2.16)	(1.82)	(0.01)
R^2				
Adj. R^2		0.32	—	0.70
χ^2 (1 df)		0.28	—	0.47
N		—	3.46	—
		523	523	81

[a] t-statistics in absolute value are in parentheses. The baseline is the following: long-run, semi-log, no addiction, no cigarette/alcohol demand system, no Almost Ideal Demand system, no smuggling, no hurdle, total cigarette consumption as the dependent variable, cross-sectional-time-series data, state/province data, not gender specific, not age specific, data covers pre- and post-1964, OLS, no error or multicollinearity correction, and not top 36 journals.

Table 4. Empirical estimates for the income elasticity[a]

Category	Variable	Model type		
		OLS	Random	Group means
Elasticity estimate	Short-run	−0.14	−0.13	−0.19
		(2.07)	(5.95)	(0.25)
Demand specification	Functional form			
	Linear	0.50	−0.05	0.34
		(1.81)	(0.32)	(0.47)
	Double-log	0.60	−0.02	0.48
		(2.25)	(0.09)	(0.69)
	Addiction			
	Myopic	−0.18	0.14	−0.30
		(−2.66)	(2.42)	(0.78)
	Rational	0.77	0.38	0.50
		(2.60)	(0.62)	(1.01)
	Other	—	—	—
	Other issues			
	Cigarette/alcohol demand system	0.66	−0.51	2.44
		(1.73)	(0.87)	(2.83)
	Almost ideal demand system	−0.14	1.10	−1.96
		(0.34)	(1.66)	(2.11)
	Smuggling	0.37	−0.88	2.15
		(1.41)	(−6.69)	(2.91)
	Hurdle	0.01	0.30	−0.02
		(0.02)	(1.16)	(0.04)
Data	Quantity			
	Tobacco	0.09	−0.09	0.14
		(1.43)	(−2.92)	(0.93)
	Per capita	0.02	−0.09	0.07
		(0.29)	(−1.04)	(0.46)
	Time-series	0.41	0.18	0.47
		(2.75)	(0.58)	(1.86)
	Cross-sectional	1.66	0.07	3.26
		(4.41)	(0.12)	(3.85)
	Aggregation			
	Country	1.04	−0.27	2.34
		(2.87)	(−0.49)	(2.82)
	Individual	−0.27	−0.55	−2.23
		(0.77)	(−1.48)	(−1.95)
	Gender			
	Men	−0.11	−0.54	0.19
		(0.77)	(−8.91)	(0.56)
	Women	—	—	—
	Age			
	Adult	−0.08	0.07	−0.16
		(0.24)	(0.51)	(0.16)
	Teen	—	—	—
	Young adult	−0.09	−0.10	15.41
		(0.17)	(0.54)	(1.67)

Table 4 (*continued*)

Category	Variable	OLS	Random	Group means
		Model type		
	Time period			
	Pre-1964	−0.02	−0.07	−0.09
		(0.15)	(0.46)	(0.48)
	Post-1964	−0.08	0.26	−0.23
		(0.83)	(0.16)	(1.33)
Estimation	Method			
	2SLS	−0.06	−0.03	−0.14
		(0.95)	(−1.03)	(0.76)
	3SLS	−0.67	−0.17	−0.89
		(4.61)	(−1.45)	(2.94)
	FIML	—	—	—
	MLE	−0.13	0.01	−0.11
		(1.13)	(0.03)	(0.53)
	SUR	0.59	−1.41	2.05
		(0.12)	(1.80)	(2.00)
	GMM	—	—	—
	GLS	—	—	—
	Corrections			
	Serial correlation			
	AR	−0.10	−0.19	1.00
		(0.92)	(5.07)	(1.98)
	MA	−0.62	−0.59	−5.51
		(−2.05)	(0.55)	(3.72)
	Heteroskedasticity	—	—	—
	Multicollinearity	0.04	−0.33	0.12
		(0.28)	(1.10)	(0.47)
Publication	Date of publication	0.01	−0.01	0.01
		(2.88)	(0.05)	(1.85)
	Top 36 Journals	0.75	0.14	0.42
		(8.12)	(0.88)	(2.09)
R^2				
Adj.R^2		0.33	—	0.75
χ^2 (1 df)		0.27	—	0.52
N		—	151.72	—
		375	375	61

[a] t-statistics in absolute value are in parentheses. The baseline is the following: long-run, semi-log, no addiction, no cigarette/alcohol demand system, no Almost Ideal Demand system, no smuggling, no hurdle, total cigarette consumption as the dependent variable, cross-sectional-time-series data, state/province data, not gender specific, not age specific, data covers pre- and post-1964, OLS, no error or multicollinearity correction, and not top 36 journals.

to reject the null hypothesis at the $p < 0.10$ or better level using a LaGrange Multiplier test (price elasticity: $\chi^2(1\text{df}) = 3.46$; income elasticity: $\chi^2(1\text{df}) = 151.72$), implying that researcher specific factors are important in the regression context. However, given the relatively small value of the test statistic for the advertising elasticity regression (i.e. $\chi^2(1\text{df}) = 0.58$), we cannot make similar inference for the advertising elasticity specification. Accordingly, rather than address

Table 5. Empirical Estimates for the Advertising Elasticity[a]

Category	Variable	Model type		
		OLS	Random	Group means
Elasticity estimate	Short-run	−0.08 (3.54)	−0.09 (4.98)	0.26 (1.76)
Demand specification	Functional form			
	Linear	−0.01 (0.21)	0.02 (0.44)	0.03 (0.41)
	Double-log	—	—	—
	Addiction			
	Myopic	0.04 (1.73)	0.04 (1.11)	0.20 (2.69)
	Rational	—	—	—
	Other	−0.09 (1.48)	−0.12 (2.29)	0.30 (1.69)
	Other issues			
	Cigarette/alcohol demand system	—	—	—
	Almost ideal demand system	—	—	—
	Smuggling	—	—	—
	Hurdle	—	—	—
Data	Quantity			
	Tobacco	−0.01 (0.12)	0.01 (0.07)	−0.02 (0.16)
	Per capita	−0.09 (2.87)	−0.09 (2.10)	−0.09 (1.83)
	Time-series	—	—	—
	Cross-sectional	—	—	—
	Aggregation			
	Country	—	—	—
	Individual	—	—	—
	Gender			
	Men	—	—	—
	Women	—	—	—
	Age			
	Adult	—	—	—
	Teen	—	—	—
	Young adult	—	—	—
	Time period			
	Pre-1964	—	—	—
	Post-1964	—	—	—

Table 5 (*continued*)

Category	Variable	Model type		
		OLS	Random	Group means
Estimation	Method			
	2SLS	0.03	0.03	0.03
		(1.35)	(1.04)	(0.49)
	3SLS	−0.07	−0.03	−0.12
		(0.99)	(0.48)	(0.64)
	FIML	—	—	—
	MLE	0.09	0.17	0.12
		(2.83)	(2.76)	(2.62)
	SUR	—	—	—
	GMM	—	—	—
	GLS	—	—	—
	Corrections			
	Serial correlation			
	AR	−0.02	−0.04	0.20
		(0.63)	(1.56)	(1.62)
	MA	—	—	—
	Heteroskedasticity	—	—	—
	Multicollinearity	−0.04	−0.05	−0.07
		(1.01)	(0.65)	(1.04)
Publication	Date of publication	−0.01	−0.01	−0.01
		(3.42)	(2.17)	(3.22)
	Top 36 journals	0.07	0.04	0.01
		(2.67)	(0.91)	(0.21)
R^2		0.41	—	0.84
Adj.R^2		0.34	—	0.58
χ^2 (1 df)		—	0.58	—
N		137	137	22

[a] *t*-statistics in absolute value are in parentheses. The baseline is the following: long-run, semi-log, no addiction, total cigarette consumption as the dependent variable, OLS, no serial correlation or multicollinearity correction, and not top 36 journals.

the empirical results of one particular model, when discussing the estimation results below we focus on general patterns across the three model types.

Below we divide the estimation results into three categories (price, income, and advertising elasticities), and discuss the results in turn, beginning with the price elasticity. Before proceeding, however, we should note two characteristics of our discussion below. First, results are always interpreted relative to the baseline (i.e. the dichotomous variables are all set equal to zero). Second, we couch our discussion of the results in a framework where positive coefficient estimates indicate an increase in the numerical elasticity estimate. Hence, in our price (income and advertising) elasticity regressions, a higher elasticity estimate implies a more inelastic (elastic) point estimate.

Price elasticity

Table 3 contains parameter estimates, measured at the sample means, for the price elasticity equations.[g] A first important finding is that via joint F-tests of the significance of the regressors in each of the five major categories, we find that the various groups significantly affect elasticity estimates at the $p<0.05$ level. Moreover, the estimated coefficients of particular variables within each of the broad categories are significantly different from zero at conventional levels. For example, following received wisdom, the demand for cigarettes tends to be more inelastic in the short-run than in the long-run (i.e. *ceteris paribus*, the short run estimates are higher than the long-run estimates).

With respect to the demand specification and data categories, several factors significantly influence the price elasticity estimates. First, the price elasticity is larger when cigarette demand is estimated jointly with alcohol demand. Second, price elasticity is lower when demand is modeled as an almost ideal demand system. Third, although significance is sparser across the three regression models, estimating a double-log specification of demand within a rational addiction framework tends to increase the price elasticity. Fourth, measuring the dependent variable as country-level tobacco consumption tends to raise the price elasticity estimate; while women (teens) tend to be less (more) sensitive to price, as indicated by the larger (smaller) price elasticity estimate.[h] Fifth, although the impact of smuggling on the price elasticity estimate is significant for the random effects and group means results, given the opposing signs of the coefficient, it is difficult to predict with confidence the likely impact of smuggling on the price elasticity.

Perhaps what is most striking about the empirical results in Table 3 are the numerous coefficients that are insignificantly different from zero, implying that price elasticity is insensitive to many factors. For instance, accounting for myopic addiction or estimating a double-hurdle model does not have a statistically significant impact on the price elasticity. Also, whether the data is time-series, cross-sectional, specific to men or young adults, or pre- or post-1964, fails to significantly affect the price elasticity. Moreover, although a few of the coefficients are significantly different from zero (particularly with respect to the OLS regression results), generally speaking estimation methods, as well as corrections for serial correlation, heteroskedasticity, and multicollinearity, have little or no impact on the price elasticity.

As for publication characteristics, we generally find that more recent studies tend to report more inelastic price elasticity estimates, as compared to earlier studies. Perhaps this is an indication that later studies extend the results of earlier studies, and thereby refine our understanding of cigarette demand. Lastly, with respect to the OLS and random effects results, we find that price elasticity estimates tend to be smaller for those studies that are published in premier (i.e. top 36) journals.

Income elasticity

Income elasticity results for all three model types are provided in Table 4.[i] Several tendencies emerge across our three specifications. First, although significance is spotty, short run estimates tend to be smaller than long run estimates. Second, income elasticity estimates tend to be greater for those studies that estimate cigarette demand jointly with alcohol demand, using either time-series or cross-sectional data (as compared to panel data) that is aggregated to the county level. Third, relative to OLS, estimating cigarette demand with three stage least squares tends to reduce the income elasticity estimate. Fourth, similar to the price elasticity results, more recent studies tend to report larger income elasticity estimates compared to earlier studies. However, unlike the price elasticity results, income elasticity estimates for those studies appearing in a top 36 journal tend to be larger. Fifth, given the lack of significance of the coefficients associated with the double-hurdle model, per capita consumption, adult- or teen-specific data, pre- or post-1964 data, 2SLS and MLE, and correction for multicolinearity, accounting for these factors in a cigarette demand model does not noticeably influence the income elasticity.[j]

Advertising elasticity

With relatively few studies having estimated the advertising elasticity of demand, the number of available advertising elasticity estimates is only 137.[k] Furthermore, as indicated in Table 2, numerous variables were excluded from the regression due to zero available observations (or all observations pertaining to a particular modeling technique, as in the case of country-level time-series data).[1] Nonetheless, to provide some insights into the role of individual factors on reported advertising elasticities, we present estimation results in Table 5.

Again, focusing on general patterns in the results, a few inferences can be drawn. First, although the group means estimate of the short-run coefficient is insignificant, for the OLS and random effects models the advertising elasticity is smaller in the short run as compared to the long run. Second, the advertising elasticity tends to be larger when a myopic addiction version of demand is estimated using MLE. Third, later published studies tend to report lower advertising elasticities compared to earlier published studies. Fourth, studies that rely on per capita consumption generally estimate smaller advertising elasticities relative to studies that rely on total consumption. Fifth, the general lack of significance for the remaining variables suggests they have little impact on the advertising elasticity.

Conclusion

The adoption of ever-improving computing technologies has fostered substantial growth in empirical research. This is particularly relevant to studies of cigarette demand, as roughly half of the studies cited herein were published within the past 15 years. Consequently, by statistically summarizing the literature to date, our meta-analysis of cigarette demand is useful in that it identifies the sensitivity of elasticity estimates to the more commonly adopted modeling techniques.

While our empirical estimates broadly support the notion that demand specification, data issues, and estimation methodology have heterogeneous influences on price, income, and advertising elasticities, there are some results common across elasticities. For example, not only are elasticities less elastic in the short run, but also the reported results are generally sensitive to the time of publication, as well as whether or not they appear in high-ranking economics journals. Accordingly, if later studies are carried out in response to earlier findings, it appears that the 'culture of the profession' has some influence on the direction and reported results of cigarette demand models. Lastly, it is important to note that our results also suggest that several modeling assumptions have a minor or statistically insignificant influence on received elasticity estimates.

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Notes

a. Specifically, we account for whether or not the journal appears in the list of the top 36 economics journals as reported in Scott and Mitias [10].
b. Myopic addiction refers to the case where consumers do not take account of the effects of current behavior on future consumption. Empirically, this is typically accounted for by the inclusion of lagged consumption in the demand model. As for rational addiction, consumers do take account of the future consequences of consumption when making decisions today, which is typically handled by the inclusion of both lagged and future consumption in the demand equation. See Grossman *et al.* [11] for a survey of the literature on addiction.
c. In reference to studies that estimate cigarette demand with cross-sectional data, smuggling can influence elasticity values. In particular, when the price of cigarettes in region *i* increases, relative to a border region *j*, consumers in region *i* that live close to region *j* may cross the border to buy their cigarettes. This causes the price elasticity to be higher (in absolute value) than what it would be otherwise. To account for this, some studies include border prices in the model [13], whereas other studies eliminate border populations when constructing the consumption variable [14].
d. Following Lewit *et al.* [15], since younger smokers have likely been smoking for a shorter period of time, they are likely to be more price sensitive than older (and more addicted) smokers. Also, in light of the volume of health information on smoking since the 1964 Surgeon General's Report, it is possible that less-addictive individuals (i.e. 'social' smokers) have exited or not entered the market, which would re-distribute demand towards a more addictive segment. This would coincide with elasticities estimated from post-1964 data being lower (in absolute value) than those estimated from pre-1964 data.
e. For example, Table 2 indicates that there are no studies that estimate the advertising elasticity and

also account for smuggling. Hence, this variable is not included in the meta-regression of the advertising elasticity.

f. One aspect associated with any meta-analysis that is oftentimes not discussed in the literature is the possibility that the data are non-randomly sampled due to, for example, published studies being more likely to be drawn (publication bias). Nuances associated with selection bias include biased coefficient estimates and *t*-statistics. Intuition would suggest that selection bias is a problem only when the error terms from the selection equation and the meta-analysis equation are correlated. Thus, one must believe that published studies have systematically different results than unpublished studies and that unobservables affecting publication are correlated with these different results. If one assumes that unpublished papers are 'correct' (and not simply rejected because the work is less than adequate), then we find it difficult to argue that the lack of publication is systematically related to the results. Yet, this issue is of course difficult to resolve, hence we follow the spirit of the meta-analysis literature and note that our findings are a representative description for the population conforming to our selection criteria, yet inference beyond this particular population is risky.

g. Since there are no observations for which 'other' methods were used to account for addiction, this variable is omitted, making the baseline correspond to those studies that do not account for addiction.

h. Our finding that cigarette consumption among teens is more sensitive to price is consistent with Lewit *et al*. [15].

i. Since observations are missing for 'other' addiction techniques, teen, FIML, GMM, GLS, and heteroskedasticity, these variables are omitted from the model. Furthermore, the regressor corresponding to women had to be dropped from the model due to violation of the rank condition.

j. For the remaining results in Table 4, because significance is more sparse (e.g. although the OLS results show significant upward pressure on the income elasticity when the model is estimated using a linear functional form, the panel and group means results show no significant impact), coupled with opposing signs of coefficients across different models (e.g. in the random effects (group means) model, accounting for smuggling decreases (increases) the income elasticity), it is much more difficult to infer general patterns from the results.

k. This is particularly noticeable in the group means results, which include only 22 observations, leading many coefficient estimates to be insignificantly different from zero at conventional levels.

l. The dichotomous variables for double-log and cigarette/alcohol demand system also had to be excluded from the equation due to failure of the rank condition.

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