

Empirical Studies of Marketing, Product Differentiation, Pricing and Competition

by

Charles King III

A.B., Harvard College (1974)

J.D., Yale Law School (1979)

Submitted to the Department of Economics
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 1997

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Abstract

Marketing plays a major role in product differentiation and competition in the prescription ulcer drug market. A variant of the discrete choice model of consumer behavior is developed that incorporates marketing by the firm and its competitors and that allows marketing to affect the scale of product differentiation. Using a panel of monthly data on four ulcer drugs from 1977 to 1993, price and marketing elasticities of demand are estimated. These results suggest: 1) marketing reduced firms' own price elasticities of demand; 2) total marketing by all firms decreased the degree of product differentiation and raised the cost of entry; and 3) marketing's effects became increasingly rivalrous.

Evidence of market power and dynamic pricing in the tobacco industry is adduced from the response of cigarette prices to changes in the age distribution of the population. Using state panel data on retail cigarette prices from 1975 to 1989 and a national time series of wholesale prices from 1950 to 1993, one finds that cigarette prices were correlated with changes in the age distribution of consumers, suggesting that the cigarette market was not then perfectly competitive. The observed positive correlation between cigarette prices and the percentage of nonsmoking children may offer tentative evidence for dynamic pricing.

Tobacco companies' advertising decisions determine adolescents' exposure to cigarette advertising in magazines. A logit analysis of 1994 cross-sectional data on where 14 cigarette brands advertise among a sample of 39 leading national magazines reveals that cigarette brands most popular with adolescents were more likely to advertise in magazines with a higher percentage of youth readers while adult brands were less likely to advertise in such magazines. These results do not appear to be consistent with the tobacco industry's claims that it does not target adolescents in its advertising.

Price and income elasticities of demand for cigarettes in New England are estimated, focussing on the importance of cross-border transactions for New England states. Based on annual time-series data from 1958 to 1992, cross-border effects are found to be statis-

tically significant factors affecting per capita cigarette sales in New Hampshire, Rhode Island, and Vermont.

Thesis Supervisor: Ernst R. Berndt, Ph.D.

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To Anne

In memoriam

Charles King, Jr. and Dorothy Ely Warden King

ωσ αρεφαν μνηστηρες: αταρ πολυητισ Οδυσσεισ, αυτικ επει μεγα τοξον εβαστασε και ιδε παντη, οσ οτ ανηρ φορμινγοσ επισταμενοσ και αιδησ ρηιδωσ ετανυσσε νεωι περι κολλοπι χορδην, απσασ αμφοτερωθεν ευστρεφεσ εντερον οιοσ, ωσ αρ ατερ σπουδησ τανυσεν μεγα τοξον Οδυσσεισ. δεξιτερηι αρα χειρι λαβων πειρησατο νευρησ: η δ υπο καλον αιισε, χελιδονι εικελη αυδην. μνηστηρησιν δ αρ αχοσ γενετο μεγα, πασι δ αρα χρωσ ετραπετο: Ζευσ δε μεγαλ εκτυπε σηματα φαινων: γηθησεν τ αρεπειτα πολυτλασ διοσ Οδυσσεισ. οττι ρα οι τερασ ηκε Κρονου παισ ανκυλομητω: ειλετο δ ωκυν οιστον, ο οι παρακειτο τραπεζηι γυμνοσ: τοι δ αλλοι κοιλησ εντοσθε φαρετρησ κειατο, των ταχ εμελλον Αχαιοι πειρησεσθαι. τον ρ επι πηχει ελων ελκεν νευρην γλυφιδασ τε, αυτοθεν εκ διφροιο καθημενοσ, ηκε δ οιστον αυτα τιτυσκομενοσ, πελεκεων δ ουκ ημβροτε παντων πρωτησ στειλειησ, δια δ αμπερεσ ηλθε θυραζε ιοσ χαλκοβαρησ.

Homer, *Odyssey*

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That there is no such thing as *one* scientist is a favorite saying of distinguished Institute Professor, Emeritus, and Professor of Physics Philip Morrison, my first teacher. “What could that person do without informed gossip, instructive news, novelties, and numbers, serious papers and books, and those enviable viewpoints occupied by others?” Science by its very nature is a social and communal activity.

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Chapter 1

Introduction

This thesis explores a broad range of empirical economic issues in marketing, product differentiation, pricing, competition and taxation. Four separate empirical essays comprise the thesis, three in industrial organization and one in public finance. The first three chapters investigate the strategic roles of marketing, pricing, and advertising in markets for prescription pharmaceutical drugs and for cigarettes. The fourth chapter estimates price and income elasticities of the demand for cigarettes in New England, focussing on the importance of cross-border transactions for the New England states.

Marketing plays a major role in the promotion of pharmaceuticals, where marketing expenditures can range as high as 10 to 20% of sales. Chapter 2 examines the role of marketing in product differentiation and competition in the ulcer drug market, one of the largest pharmaceutical markets. A variant of the discrete choice model of consumer behavior is developed that incorporates the effects of marketing by the firm and its competitors and that allows marketing to affect the scale of product differentiation. Using a panel of monthly data on four ulcer drugs from 1977 to 1993, the price and marketing elasticities of demand are estimated. These results suggest three primary effects of marketing during this period. First, marketing reduced firms' own price elasticities of demand. Second, total marketing by all firms reduced the degree of product differentiation in the market and raised the cost of entry to potential competitors. Third, marketing

initially expanded the market for ulcer drugs but later became an increasingly important means of stealing business from competitors.

The next two chapters consider the economic and public health issues of cigarette smoking, the leading cause of preventable deaths in the United States. An estimated one million U.S. adolescents start smoking each year, and about half will continue to smoke into adulthood. Nearly half of those who continue to smoke will eventually die from their cigarette use. Chapters 3 and 4 examine whether cigarette manufacturers target the young either through their pricing or through their marketing policies.

Chapter 3 tests for market power and dynamic pricing effects in the cigarette industry by investigating whether cigarette prices respond to the changing age distribution of U.S. and state populations, while controlling for other factors that affect demand or costs. Competitive firms produce to equate price to marginal cost. But firms with market power will adjust their prices according to the relative proportion of young to old smokers since they have different price elasticities of demand. If these firms optimize dynamically, they will also account for the number of young children, who do not now smoke but may in the future, and for the ratio of middle-aged to older smokers in setting prices.

These hypotheses are tested using state panel data on retail cigarette prices from 1975 to 1989 and a national time series of wholesale prices from 1950 to 1993. Evidence from both data sets that cigarette prices were correlated with changes in the age distribution of consumers, in particular the proportion of young to old, suggests that the cigarette market may not have been perfectly competitive during these time periods. Furthermore, the observed positive correlation, which apparently cannot be explained by differences in elasticities among subgroups of the population, between cigarette prices and the percentage of nonsmoking children offers tentative evidence that dynamic pricing may play a role in the market for cigarettes.

Chapter 4 is written with coauthors Michael Siegel, M.D., M.P.H., Carlolyn Celebucki, Ph.D., and Gregory N. Connolly, D.M.D., M.P.H. for a medical and public health audience, whose style and conventions differ from those of economists. The chapter

examines adolescents' exposure to cigarette advertising in magazines and assesses the impact of new FDA prohibition of cigarette advertising in certain magazines with high youth readerships. The 1994 Surgeon General's report implicated the advertising and promotion of cigarettes as one cause of smoking initiation among adolescents. Of all the media by which cigarettes are advertised — newspapers, magazines, outdoor, and transit — magazines receive the largest share of tobacco company expenditures. In 1994, the tobacco industry spent \$252 million, or 46% of its total cigarette advertising budget, on advertising in magazines.

The chapter analyzes tobacco companies' decisions about where to advertise their youth and adult brands in major national magazines. The logit analysis uses a 1994 cross-sectional data set on: (1) the distribution of advertising for 14 cigarette brands among a sample of 39 top U.S. magazines; (2) youth and adult readership and other demographic information for each magazine; and (3) the cost of advertising in each magazine.

The results obtained from this data set do not appear to be consistent with the tobacco industry's claims that it does not target youths and adolescents in their advertising. The relationship between advertising and youth readership was significantly different for cigarette brands that were smoked by more than 2.5% of 10 to 15 year-old smokers in 1993 ("youth" brands) compared to brands smoked by less than 2.5% of 10 to 15 year-old smokers ("adult" brands). After controlling for the total readership and the cost of advertising for each magazine, youth brands were more likely to advertise in magazines with a higher percentage of youth readers. In contrast, adult brands were less likely to advertise in magazines with higher youth readership. The observed differences in the relationship between advertising and youth readership for adult and youth brands persisted after controlling for the percentage of young adult (ages 18-24) magazine readers.

The final chapter investigates an issue of public finance and public health concern: the price and income elasticities of the demand for cigarettes in New England, focussing on the importance of cross-border transactions for the New England states. Based on

annual time-series data from 1958 to 1992, cross-border effects are found to be statistically significant factors affecting per capita cigarette sales in New Hampshire, Rhode Island, and Vermont. These results imply that these states should account for the excise tax rates in adjacent states when setting their own revenue and public health policies. The presence of significant cross-border effects also means that federal cigarette excise taxes will be both more efficient in generating revenue and more effective as an instrument of public health policy than state taxes.

Chapter 2

Marketing, Product Differentiation, and Competition in the Pharmaceutical Industry

With worldwide sales in 1995 of \$116.6 billion and an annual growth rate of 17.2%, pharmaceutical drugs are a vast and growing industry (Chappell 1995). Since these revenues represent more than one and a half percent of the U.S. gross domestic product, the pharmaceutical industry commands a significant position in the economy. In the vast market for pharmaceuticals, marketing constitutes a major competitive force by which firms strive to differentiate their products and soften price competition.

Three aspects of the pharmaceutical industry make it ideally suited for studying the role of marketing in product differentiation. First, pharmaceutical firms spend an unusually large percentage of their revenues promoting their products. Advertising for over-the-counter drugs amounts to about 20% of sales, making them the most heavily promoted of all manufactured goods. This stands in sharp contrast to advertising in the median manufacturing industry, which devotes less than 1% of its sales revenues to advertising (Scherer and Ross 1990). Marketing efforts for the ulcer drugs that form the subject of this study comprise roughly 10% of sales. Second, pharmaceutical companies

largely concentrate their marketing efforts in a single form of marketing, visits to doctors' offices, which simplifies the analysis of marketing's effects. Finally, drugs have essentially fixed characteristics determined by the chemical properties of the particular molecule that constitutes the drug. Since FDA approval is required to change the dosage frequency or other physical characteristics of a drug, this limits the ability of pharmaceutical companies to compete against each other strategically by changing the characteristics of their products.

Despite the importance of marketing, most recent studies of the pharmaceutical industry have focussed on the effects of entry by generic drugs, *e.g.*, Caves, Whinston, and Hurwitz (1991), Hellerstein (1994), Hurwitz and Caves (1988) and Scott Morton (1994). Relatively few studies examine the demand for branded pharmaceutical drugs, *e.g.*, Ellison, Cockburn, Griliches, and Hausman (1994) and Stern (1994), and even fewer investigate the role of marketing, with the notable exception of Berndt *et al.* (1995, 1997). Many questions of strong empirical interest therefore remain largely unanswered. How does marketing affect the degree of product differentiation? Does a firm's marketing make its demand more inelastic? Is the effect of marketing primarily to expand the market or to steal business from competitors? And, finally, does marketing raise the costs of entry to potential competitors?

To address these and related questions, this chapter develops a discrete choice model of consumer behavior that incorporates the effects of marketing by the firm and its competitors and that allows marketing to affect the scale of product differentiation. This approach enables one to estimate effects of marketing that previously were difficult to measure. The proposed model allows for the estimation of its parameters using routine econometric techniques without requiring the sophisticated and computationally intensive numerical techniques of the related random coefficients models of Berry (1994) and Berry, Levinsohn, and Pakes (1995). The model is then applied to analyze marketing in the specific context of the market for prescription ulcer medications.

Among all prescription drugs, one of the largest segments during the period studied

was the class of ulcer drugs known medically as H₂-receptor antagonists,¹ which includes the world's then largest selling drug, Zantac, with estimated worldwide revenues of \$3.5 billion in 1992. This research, based on monthly panel data on four ulcer drugs from 1977 to 1993, yields several findings about the effects of marketing in the ulcer drug market. Marketing by both the firm and its competitors significantly affected the demand for ulcer drugs. A firm's own marketing made its demand more price inelastic, which *ceteris paribus* would allow it to raise prices. Total marketing by all firms apparently reduced the degree of product differentiation in the ulcer drug market and raised the cost of entry to potential competitors. Finally, over the sample period, the role of marketing shifted from market expansion to business stealing as marketing became less effective in attracting new customers and more important as a means of capturing customers from rival firms.

This chapter contains seven sections. The first provides a brief description of the market for ulcer drugs. Section 2 incorporates marketing in a discrete choice model of demand. Section 3 describes the data used to estimate the model, and Section 4 discusses the estimation and the instrumental variables. The main findings of the chapter comprise Section 5. Section 6 explores the role of marketing in product differentiation and competition through a series of simulations. Section 7 contains the conclusion.

2.1 The Market for Ulcer Drugs

One of the largest segments of the pharmaceutical market consists of the class of ulcer drugs known as H₂-receptor antagonists. These revolutionary drugs promote the healing of ulcers by reducing acid secretion in stomach.² The spectacular success of the H₂-

¹The histamine-2 (H₂) hormone is one of three messenger molecules that trigger gastric acid production. These drugs act by blocking the receptor for H₂ and thus reduce acid secretion in the stomach.

²There are several types of ulcers and digestive disorders for which these drugs are effective treatments. Ulcers located in the stomach are called gastric ulcers. Duodenal ulcers occur in the duodenum, a bulb connecting the stomach to the small intestine. GERD is an acronym for a related non-ulcerous condition known as gastroesophageal reflux disease that affects the esophagus and manifests itself as severe heartburn. All these conditions involve an inflammation of tissue in the digestive tract that is exacerbated by the body's production of gastric acid. Since H₂-receptor antagonists reduce stomach acid secretion, they are effective in relieving the symptoms of these diseases.

Drug	Chemical Name	Manufacturer	First Approval	First Sales
Axid	Nizatidine	Lilly	April 1988	May 1988
Pepcid	Famotidine	Merck	October 1986	November 1986
Tagamet	Cimetidine	SmithKline	August 1977	August 1977
Zantac	Ranitidine	Glaxo	June 1983	June 1983

Table 2.1: Ulcer Drug Summary.

receptor antagonists following Tagamet's introduction by SmithKline in 1977 arose from their ability to treat ulcers and pre-ulcerous conditions pharmacologically on an out-patient basis, replacing the need for the expensive hospital admissions and surgeries of traditional therapies. Since 1977 three other H₂-receptor antagonists have entered the market for ulcer drugs: Zantac (Glaxo) in 1983, Pepcid (Merck) in 1986, and Axid (Lilly) in 1986. Figure 2-1 shows the evolution of the relative shares of these four ulcer drugs over time, while Figure 2-2 shows the monthly flows of the firms' marketing efforts measured in terms of the time spent by sales representatives in doctors' offices promoting a particular drug. The large spikes in marketing levels correspond to the entry of new drugs and approvals for new indications and reveal the competitive responses of firms in the market to these events. A brief overview of the panel data and history of the H₂-receptor antagonist drugs appears in Tables 2.1 and 2.2. Table 2.1 lists the trade and chemical names for each drug, its manufacturer, date of first FDA approval, and first sales date. Table 2.2 is a complete list of all FDA approvals for specific indications and their dates.

2.2 A Model of Product Differentiation

This section develops a discrete choice model of marketing and product differentiation that will be used to assess the effects of marketing on competition in the market for ulcer

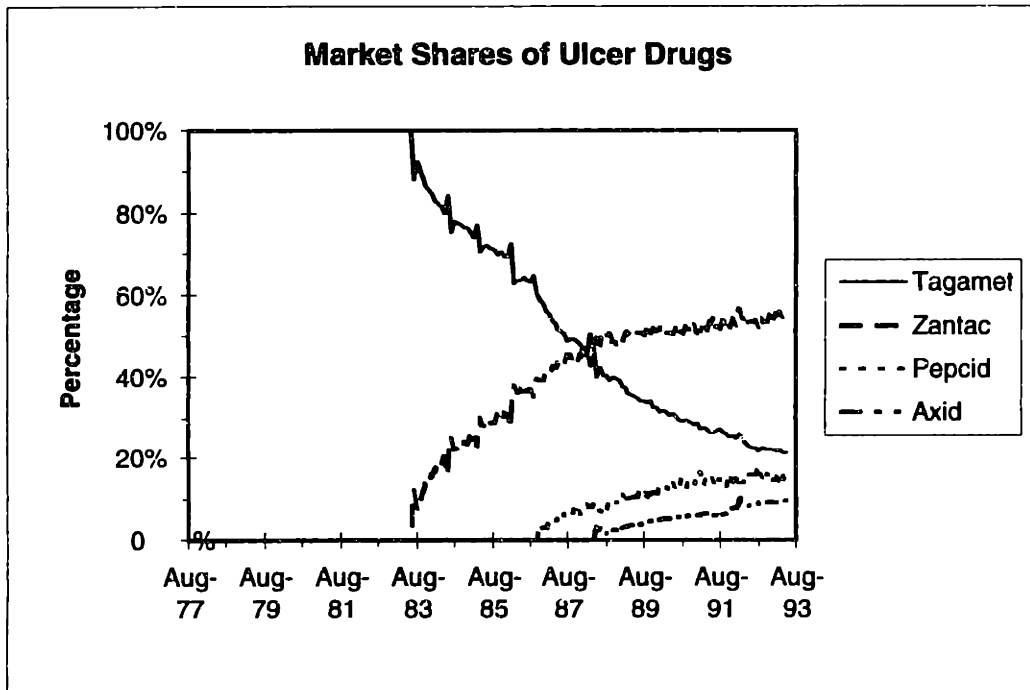


Figure 2-1: Market Shares of Ulcer Drugs

Drug	Duodenal Ulcer	Duodenal Ulcer Maintenance	Gastric Ulcer	GERD	Stress Ulcer Ulcer Prophylaxis
Axid	Apr 1988	Apr 1988		Jul 1991	
Pepcid	Oct 1986	Oct 1986	Oct 1988	Dec 1991	
Tagamet	Aug 1977	Apr 1980	Dec 1982	Mar 1991	Nov 1991
Zantac	Jun 1983	May 1986	Jun 1985	May 1986	

Table 2.2: FDA Indication Approval Dates for Ulcer Drugs.

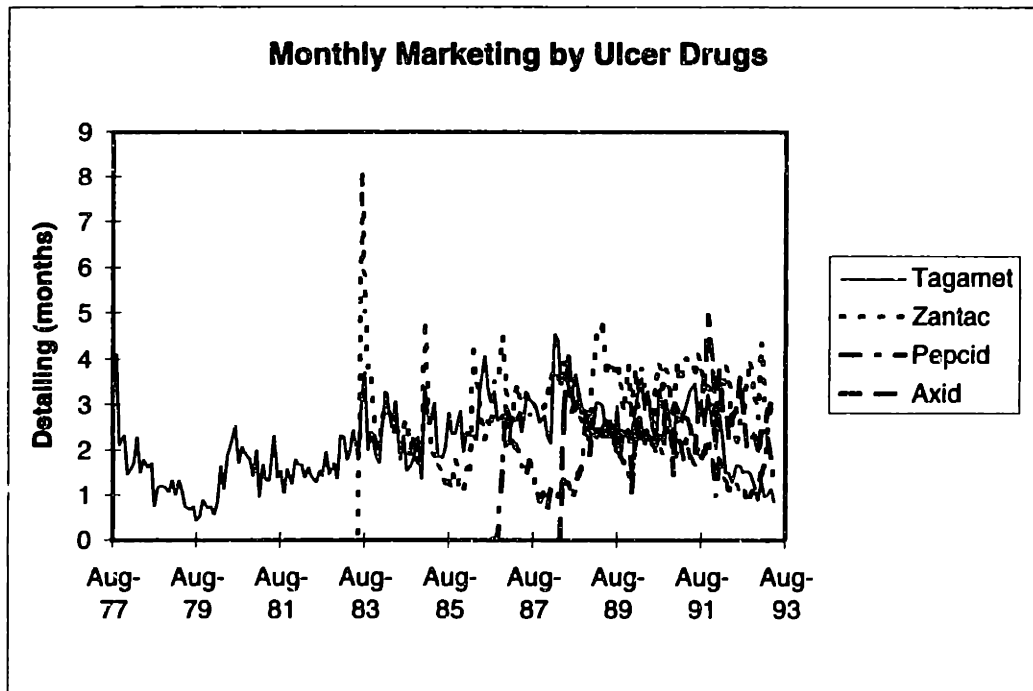


Figure 2-2: Monthly Marketing by Ulcer Drugs

drugs. In the discrete choice model, each consumer selects the product that maximizes the consumer's individual utility. Product characteristics and consumer preferences form the primitives of the model, and consumer utility is a function of these primitives. Each firm produces a single good, and all goods are substitutes. The discrete choice model offers several benefits: the derived demand equations are consistent with consumer theory, consumer heterogeneity is easily incorporated, and the entry of new products is easily assimilated by the model. In applying this model to the demand for prescription drugs, however, one should keep in mind that the physician, as the patient's agent, selects the drug to be administered and not the patient as the consumer.³

To analyze how marketing affects product differentiation and competition, three distinct effects of marketing are included in the discrete choice model. First, firm j 's marketing efforts, M_j , presumably increase the probability that consumers select product j

³This may lead to a potential principal-agent problem that is beyond the scope of this paper.

over its competitors. Second, the marketing by firm j 's competitors, M_{-j} , by increasing the probability that consumers select other products, may decrease the probability that consumers choose firm j 's product. Third, the total marketing efforts of all firms, M_{tot} , may also influence consumers' perceptions of the degree of product differentiation in the market itself. To capture the first two effects of marketing, both firm j 's and its competitors marketing are included among the characteristics of product j . The third effect is incorporated by allowing the distribution of consumer preferences to vary with total marketing. Whether the total marketing by all firms increases the overall size of the market depends on the relative importance of the market expansion and business stealing that result from individual firms' marketing efforts.

In the standard discrete choice model of consumer choice, such as that analyzed by Anderson, de Palma, and Thisse (1992) and Berry (1994), a large number of consumers, labelled $i = 1, \dots, N$, choose from a set of products, denoted $j = 0, \dots, J$.⁴ Each consumer selects the product that provides the most utility. The utility that consumer i derives from consuming product j is a function of the observable characteristics of the product, $X_j \in \mathbb{R}^K$, including marketing by the firm, M_j , and its competitors, M_{-j} , the price of the product, p_j , and the unobserved idiosyncratic preference, ε_{ij} , of consumer i for product j . Assume that this utility can be represented as

$$u_{ij}(\mathbf{X}, \boldsymbol{\theta}) = X_j' \boldsymbol{\beta}_i - \alpha p_j + \tilde{\xi}_j + \varepsilon_{ij}. \quad (2.1)$$

Here $\boldsymbol{\theta} = \{\alpha, \boldsymbol{\beta}\}$ is the set of parameters of the utility function, the ε_{ij} have mean zero, $E[\varepsilon_{ij}] = 0$, and the $\boldsymbol{\beta}_i$ capture the differences in consumer preferences for different product characteristics. The independent variable $\tilde{\xi}_j$ embodies the mean consumer utility derived from a set of product characteristics, other than the X_j , which are observed by consumers but not econometricians. Define the mean consumer utility level for product

⁴In this framework, one good plays a special role. The outside good, usually denoted as $j = 0$, represents the alternatives to choosing one of the specific goods, $j = 1, \dots, J$, in the model.

j as

$$\delta_j \equiv X_j' \beta - \alpha p_j + \bar{\xi}_j. \quad (2.2)$$

Then the ε_{ij} of equation 2.1 represent the distribution of individual consumer preferences about this mean.

2.2.1 Product Differentiation and the Scale Parameter

Assume, for the moment, that the ε_{ij} are independently and identically distributed across products and among consumers, and let σ be the variance of ε_{ij} . Note that σ , the width of the preference distribution, determines the degree to which the products are differentiated and provides the metric that measures the degree of product differentiation as illustrated in Figure 2-3. Figure 2-3 graphs the distribution of consumer preferences for two products with mean consumer utilities δ_j and δ_k . Utility increases to the right while the vertical axis denotes the number of consumers. For small σ , consumer preferences cluster tightly about the mean utility of each product. The two solid curves centered on δ_j and δ_k in Figure 2-3 represent distributions with variance σ_1 of consumer preferences about the mean consumer utility for products j and k . If consumers have more heterodox preferences, their distribution about the mean utility of the product is broader as for the distribution labelled σ_2 drawn with a dashed line in the figure.

Consider now the distribution with the smaller variance, σ_1 . Since there is no overlap of the upper right tail of the distribution of consumer preferences about δ_j with the lower tail of the corresponding distribution about δ_k , no consumer has such a high idiosyncratic preference for product j and such a low one for product k that this consumer would choose product j over product k . In this case, the population of consumers sharply distinguishes these two products: since product k has higher mean utility δ_k , all consumers choose product k over product j .

Compare this with the case where consumer preferences are more diverse and have a larger variance σ_2 shown as the dashed curves in Figure 2-3. Now the upper tail of the

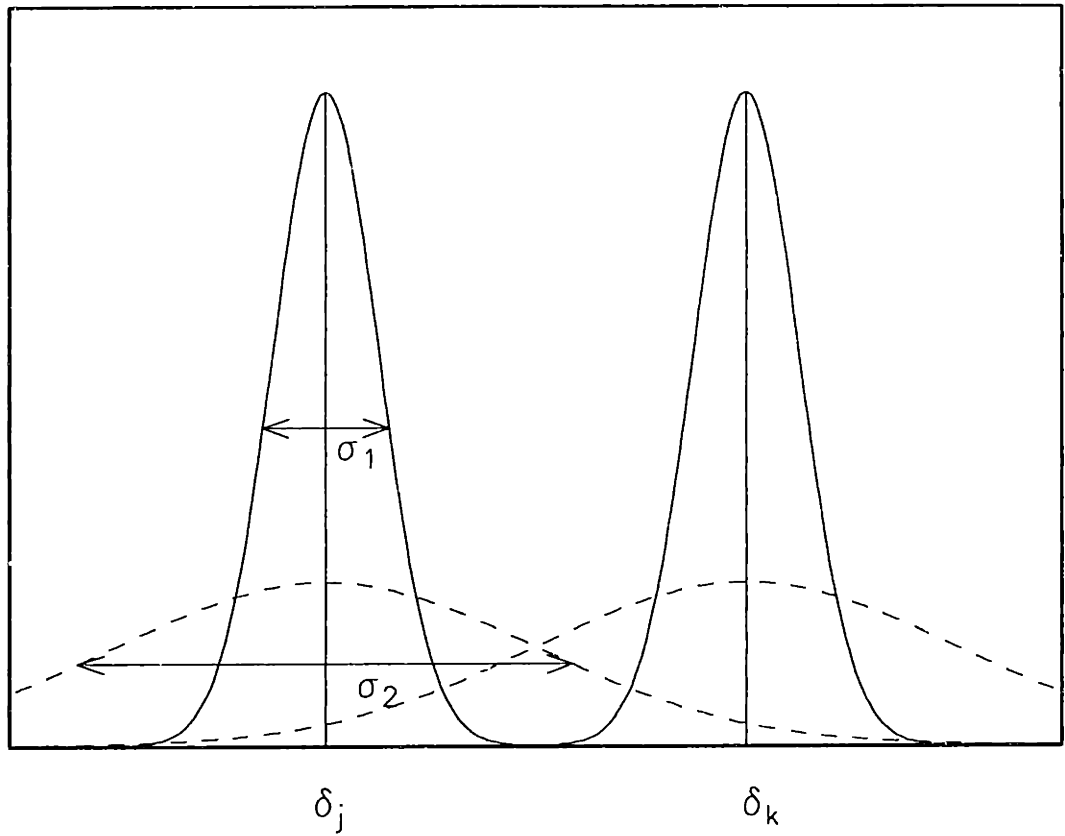


Figure 2-3: The Variance of the Consumer Preference Distribution Determines the Scale for Product Differentiation.

distribution of consumer preferences about δ_j overlaps the lower tail of the distribution centered on δ_k . Some consumers have sufficiently high personal preferences for product j and sufficiently low preferences for product k that they will choose product j over k even though product k has a higher mean utility, $\delta_k > \delta_j$. In this case, the two products are not as clearly differentiated by consumers as in the previous case: even though product k has a higher mean utility than product j , some consumers will choose product j . Since the variance, σ , of the distribution of consumer preferences determines the scale for measuring product differentiation, one can consider how firms' marketing efforts influence consumer preferences and hence the degree of product differentiation in the market.

Given a set of products and their prices, consumer i chooses the product yielding the greatest utility. This implicitly defines the set of unobservable taste parameters, ε_{ij} , that result in the selection of good j . Denote this set as $A_j(\boldsymbol{\delta}) = \{\varepsilon_{ij} \mid \delta_j + \varepsilon_{ij} > \delta_k + \varepsilon_{ik}, \forall k \neq j\}$. The market share of firm j is then simply the probability that ε_{ij} lies in the set A_j . Let ε_{ij} have a probability density function, $f(\cdot, \mathbf{X}, \sigma)$, which may depend explicitly on the characteristics, \mathbf{X} , of the products and where σ is now the scale parameter, and not necessarily the variance, of the distribution. The market share is then given by the integral of the density function over A_j ,

$$s_j(\boldsymbol{\delta}(\mathbf{X}), \mathbf{X}, \boldsymbol{\theta}) = \int_{A_j(\boldsymbol{\delta})} f(\boldsymbol{\varepsilon}, \mathbf{X}, \sigma) d\boldsymbol{\varepsilon}, \quad (2.3)$$

where $\boldsymbol{\theta}$ is the set of model parameters.⁵

⁵Berry (1994) has shown that under weak regularity conditions and conditional on setting the mean utility of the outside good, δ_0 , to zero, the vector-valued market share equation $\mathbf{s} = s(\boldsymbol{\delta})$ is bijective. Given any density function $f(\cdot, \mathbf{X})$, the observed market shares can be inverted to recover the unique vector of mean utilities $\boldsymbol{\delta} = s^{-1}(\mathbf{s})$.

When the distribution of $\boldsymbol{\varepsilon}$ is known, the only unknown parameters in the market share function $\mathbf{s}(\boldsymbol{\delta})$ (equation 2.3) are the mean utilities $\boldsymbol{\delta}$. Treating the unique, calculated mean utility levels, $\boldsymbol{\delta}(\mathbf{s})$, as a known, nonlinear transformation of the original market share data, \mathbf{s} , results in a simple estimation procedure since for the true values of $\boldsymbol{\beta}$, $\delta_j = X_j\boldsymbol{\beta}$. Standard instrumental variables techniques can then be used to obtain estimates of the true parameters. Except for the computational difficulty of inverting the market share function, this equation simply involves a transformation of the original data as a dependent variable.

Assuming that the β do not vary across consumers – that is, that all consumers value the observable characteristics the same while still deriving an idiosyncratic amount of utility, ε_{ij} , for each product – a simple model for product choice can be derived. If ε_{ij} is independently and identically distributed with an extreme value distribution, the market share of product j is given by the logistic transformation

$$s_j(\delta_j) = \frac{\exp(\frac{\delta_j}{\sigma})}{\sum_{k=0}^N \exp(\frac{\delta_k}{\sigma})}, \quad (2.4)$$

where σ is now the scale parameter of the distribution whose variance is $\pi^2\sigma^2/6$.

At this point in the derivation of the simple logit model, the scale parameter σ is ordinarily normalized away by rescaling the utility function. Under the assumption that σ is constant, one is free to normalize equation 2.4 since utility is invariant under an affine transformation.⁶ But the assumption that σ is constant may not be appropriate for studying the effects of marketing on demand, product differentiation, and competition since the value of σ determines the scale of product differentiation. If one is interested in the degree to which the total marketing efforts of all firms, M_{tot} , affect product differentiation, one must consider how total marketing influences σ .⁷ The specific choice of functional form for σ is deferred until section 2.4 where the estimation of the model is discussed. For σ as a function of M_{tot} , taking the ratio of two shares implies

$$\begin{aligned} \ln(s_j) - \ln(s_k) &= \frac{1}{\sigma(M_{tot})} (\delta_j - \delta_k) \\ &= \frac{1}{\sigma(M_{tot})} \left[(X_j - X_k)' \beta - \alpha(p_j - p_k) + (\tilde{\xi}_j - \tilde{\xi}_k) \right]. \end{aligned} \quad (2.5)$$

⁶As part of the normalization, the mean utility of the outside good, δ_0 , is also typically set to zero so that the coefficients β can be identified.

⁷But note that σ then affects all consumer preference distributions the same way. That is, the variance of consumer preferences about the mean utilities of all products is the same. Relaxing this condition simply leads to a random coefficients model, such as that estimated by Berry, Levinsohn, and Pakes (1995), Nevo (1996), and others.

Normalizing the mean utility of the outside good to zero, this simplifies to

$$\ln(s_j) - \ln(s_0) = \frac{\delta_j}{\sigma(M_{tot})} = \frac{1}{\sigma(M_{tot})} \left(X_j' \beta - \alpha p_j + \tilde{\xi}_j \right). \quad (2.6)$$

These last two equations contain both the direct effects of marketing on demand and its indirect effect on demand through the scale of product differentiation. If a firm j 's own marketing, M_j , and that of its competitors, M_{-j} , are each included among the characteristics, X_j , the corresponding coefficients will measure their direct contributions to the product's mean utility and hence its demand. Now consider a given difference, $(\delta_j - \delta_k)$, in the mean utility levels experienced by consumers from consuming products j and k . The larger σ is, the larger is variance in the underlying consumer preferences, the more difficult it is for consumers to distinguish between product j and product k , and the closer are their respective market shares, s_j and s_k . The smaller the variance, the more readily consumers distinguish small differences in mean utilities, $(\delta_j - \delta_k)$, as shown in Figure 2-3 and equation 2.5.

The effect of total marketing, M_{tot} , on product differentiation and competition depends on whether $\sigma(M_{tot})$ is an increasing or decreasing function. If $\sigma'(M_{tot}) > 0$, an increase in total marketing *decreases* the amount of product differentiation and *intensifies* product competition in the market. Conversely, for $\sigma'(M_{tot}) < 0$, raising total marketing acts to differentiate products further and to reduce competition between products. Through this mechanism, total marketing may also raise or lower the costs of entry by frustrating or facilitating product differentiation. For example, if σ increases with total marketing, existing products are forced to compete more fiercely with each other as total marketing increases. A potential entrant, with a given set of characteristics, will have to work harder – by reducing its price or increasing its own marketing efforts, for example – to achieve the same market share as it would have achieved at a lower level of total marketing. Alternatively, if σ decreases with total marketing, an increase in marketing heightens product differentiation and may facilitate entry by potential competitors who now find it easier to distinguish their products from the existing ones.

2.3 Data

The estimation of the market share equation, equation 2.6, requires information about the size of the total market, Q , product characteristics, X_j , (including own and competitors' marketing efforts, M_j and M_{-j} respectively), total marketing, M_{tot} , and prices, p_j . This study uses an extensive set of monthly data for the four H₂-receptor antagonist drugs, Tagamet, Zantac, Pepcid and Axid, that spans the nearly sixteen years from August 1977 to May 1993. These data were originally collected by Berndt, Bui, Reiley, and Urban (1995) who generously provided their data for this research.⁸ Summary statistics for the panel are reported in Table 2.3.

Market data on prices, quantities, and marketing efforts originated with IMS America, a Philadelphia-based private company that tracks the sale and marketing of pharmaceutical products and is the principal source of information about the pharmaceutical industry. Two IMS publications, the *IMS Annual Hospital and Drugstore Audits* and the *IMS Personal Selling Audit*, provided the market data for the ulcer drugs. Coverage by IMS of wholesale pharmaceutical sales from distributors to pharmacies and hospitals is extensive.⁹ According to IMS, its drugstore audit includes 67% of the United States pharmaceutical market and its hospital audit covers an additional 16%.

Since the ulcer drugs are different molecules with different dosages and are sold in different presentational forms, a common basis for comparison must be created. For each presentational form, *e.g.*, bottles of 50 tablets of 40 milligrams each, the total milligrams of the drug and the average per milligram price are computed. These quantities and nominal prices are then converted into patient days and prices per patient day using the recommended daily dosage for duodenal ulcer treatment as the conversion factor. The use of a standard dosage enables comparison of drug prices and quantities across molecules, presentations, and manufacturers. To convert nominal quantities to real amounts, all

⁸Berndt, Bui, Lucking-Reiley, and Urban (1997) discuss the nature of the IMS data in detail and provide a useful data appendix.

⁹The IMS data do not include sales to foodstores, dispensing physicians, health maintenance organizations, mail order firms, nursing homes, prescription management programs or clinics.

Variable	Mean	Standard Deviation	Minimum	Maximum
Ln (s_j/s_0)	-1.60	0.90	-4.714	-0.007
Age	67.6	48.8	1	190
Frequency	1.7	1.2	1	4
Interactions	3.1	4.1	0	10
Own Marketing*	0.35	0.15	0	0.624
Others' Marketing*	0.81	0.53	0	1.558
Total Marketing*	1.16	0.60	0	1.891
Indications	2.84	1.06	1	5
Price	1.32	0.34	0.40	1.86

* Depreciated at 4.6% per month. The units are 10 years (5.2596×10^6 mins) of detailing.

Table 2.3: Summary Statistics for the Characteristics of Ulcer Drugs.

prices are deflated by the monthly consumer price index.

Each drug in the sample is a unique chemical entity with specific characteristics. Those most important to prescribing physicians include the indications for which the FDA has approved the drug, the recommended daily dosage and dosage frequency, the number of adverse drug interactions, and the age of the drug (Suslow 1993). Information on drug characteristics was obtained from various annual issues of the *Physician's Desk Reference* and the *U.S. Pharmacopeia Convention, Dispensing Information*. The age of each drug is computed as the number of months the drug has been on the market.

Since the dependent variable in the equation to be estimated is expressed in market shares, the size of the total market is required to compute each product's quantity market share with respect to the total market. In this model, the market size is assumed to be exogenous. The total market is defined as a therapeutic market based on estimates of the incidence of ulcers and related conditions (Yamada 1995), and is taken as 2.7% of the total United States population as measured by the *Census*.¹⁰

Marketing plays a key role in the promotion of pharmaceuticals. The dominant method of marketing is through visits to doctors' offices by sale representatives from manufacturers, known in the trade as "detailing". Detailing represents approximately 70% or more of all marketing expenditures (Berndt, Bui, Lucking-Reiley, and Urban 1997). IMS collects monthly information on the number of visits and minutes spent with sales representatives discussing a particular drug from a panel of some 3,000 physicians. As a measure of firms' efforts in marketing and promoting their products, this study uses the number of detailing minutes as the quantity measure of the flow of firms' marketing efforts. Since the effects of firms' marketing efforts may decline over time, the estimations allow for a depreciation rate of marketing. All depreciated stocks of marketing efforts are calculated using the same estimated depreciation rate.

In the next section, these data are applied to the estimation of the demand for ulcer

¹⁰Although specific parameter estimates will vary as a function of market size, the qualitative results are not sensitive to the choice of the size of the total market.

drugs.

2.4 Estimation

To estimate the model, one must specify a functional form for the scale parameter, σ , for the distribution of consumer preferences. The scale parameter used for the estimations is:

$$\sigma (M_{tot}) = (1 + \gamma M_{tot})^2, \quad (2.7)$$

where the total marketing efforts are $M_{tot} = M_j + M_{-j}$. Many other specifications are possible, and several are discussed in the next section. This particular functional form for σ , which insures that the variance remains positive, was chosen because it is robust to estimating a number of different models that were used to check this specification as discussed in the following section. But, in fact, for total marketing, a linear, first order expansion gives results similar to those for the above specification.

Using the previously described data on the size of the total market and the particular characteristics of each drug, one can now estimate the market share equation. Indexing time by t and expressing the market share equation in terms of the data variables, the equation to be estimated becomes

$$\begin{aligned} \ln(Share_j/Share_0)_t = & \left[\frac{1}{(1 + \gamma * (TotalMarketing)_t)^2} \right] (\beta_0 + \beta_1 * (Age)_t \\ & + \beta_2 * (Frequency)_t + \beta_3 * (Interactions)_t \\ & + \beta_4 * (OwnMarketing)_t + \beta_5 * (OthersMarketing)_t \\ & + \beta_6 * (Indications)_t + \beta_7 * (Price_j)_t \\ & + \beta_8 * (Zantac)_t + \beta_9 * (Pepcid)_t \\ & + \beta_{10} * (Axid)_t + \Delta\xi_{jt}), \end{aligned} \quad (2.8)$$

where

TotalMarketing is the number of minutes of detailing by all firms selling H₂-receptor

antagonist ulcer drugs,

Age is the number of months the drug has been on the market,

Frequency is the number of times per day the drug must be taken,

Interactions is the number of adverse reactions the ulcer drug has to other drugs,

OwnMarketing is the number of minutes of detailing undertaken by the firm in promoting its drug,

OthersMarketing is the sum of number of minutes of detailing by all the drug's competitors,

Indications is the number of indications for which the FDA has approved the drug,

Price is the average wholesale price to drugstores for a patient day of therapy at the standard dose for a duodenal ulcer, and

Zantac, *Pepcid*, and *Axid* are dummy variables for each of those drugs.¹¹

Note that the error term, $\tilde{\xi}_j$, representing the mean utility to consumers from unobserved product characteristics, in the share equation, equation 2.6, has been decomposed into two parts, $(\tilde{\xi}_j)_t = \xi_j + \Delta\xi_{jt}$. The first of these, ξ_j , is the mean utility to consumers averaged over all time periods, t , and is now picked up by the coefficients on each of the separate product dummy variables in the above equation. The second term, $\Delta\xi_{jt}$, represents variations over time about this mean utility and is the source of the error in the estimating equation. One can think of this error as representing changes in doctors' average valuation of drug j as the population of doctors and standards of practice change.

Since the price, p_j , may be correlated with changes in the unobserved product characteristics, $\Delta\xi_{jt}$, and since both price and marketing expenditures, as strategic instruments of the firm, are endogenous, the estimation of the model's parameters may require a set of instrumental variables, Z . Given that the market share equation is nonlinear, the need for instrumental variables leads naturally to a generalized method of moments (GMM)

¹¹One may also include market structure dummy variables for the number of firms in the industry as an alternative specification. Note that this specification is functionally equivalent to that given above.

estimation with conditional moment restrictions,

$$E[Z \cdot \Delta\xi_{jt}] = 0, \tag{2.9}$$

to obtain estimates of the relevant parameters.

2.4.1 Instrumental Variables

The estimation of the model's parameters employs a variety of instrumental variables to alleviate the possible endogeneity of prices and marketing. One set of variables is common to all the firms in the sample: the producer price index for intermediate materials, the wage rate for production workers in the pharmaceutical industry, and a linear time trend. Another group incorporates firm level variations using data from the separate hospital market for these drugs and measures of the level of competition in the market.

Ideally, one would like to use sources of variations in marginal cost across firms as instrumental variables in the demand equation. But in the pharmaceutical industry, marginal manufacturing costs are small and unobserved, and the standard cost-shifting instruments for an individual drug are unavailable.

Another source of instrumental variables lies in price data from other, distinct markets. For these drugs, the hospital and drugstore markets are almost entirely independent. Consumers cannot easily substitute between them, and the hospital use of H₂-receptor antagonists differs substantially from the outpatient use. Hospitals primarily administer these drugs intravenously to reduce the acid secretion induced by trauma in emergency room patients, to counteract the side effects arising from large doses of nonsteroid analgesics, and in conjunction with anesthesia required for surgery. Drugstores, by contrast, sell primarily oral preparations to alleviate ulcers in otherwise healthy patients. Since the hospital and drugstore markets should experience the same manufacturing costs shocks, hospital prices are used as instrumental variables for drugstore prices for the drugs under study. While an epidemic common to both markets seems unlikely, favorable news about

the efficacy of a particular drug might create the same demand shocks in both markets, which would undercut the validity of hospital prices as instrumental variables. However, the nominal price series for each the four drugs reveal that price changes occur only infrequently, over periods of six months to a year and occasionally longer. This suggests that drug prices may be predetermined and difficult to change, which would reduce the need for instrumental variables.

The number of detailing minutes spent by each firm marketing its non-ulcer drug products is used as an instrument for the firms' marketing efforts on behalf of the ulcer drugs. One potential problem is that this choice assumes firms set a marketing budget and fix the allocation of marketing for these drugs or that changes in ulcer drug marketing do not affect the marketing budgets for other products.¹² A second problem may arise from Glaxo's tremendous success with Zantac which comes to dominate the firm and its marketing efforts.

The number of firms in the market is used as an instrumental variable measuring the level of competition in the market under the assumption that entry, which the Federal Food and Drug Administration controls, is exogenous.¹³ As the number of firms and the differentiation between products change, firms will alter their pricing and marketing policies. This should help identify variations in price and marketing that are uncorrelated with the error in the demand equation.

In summary, since marketing efforts, pricing, and quantity demanded are likely to be endogenous, eight instrumental variables were employed in estimating the regression equation 5.1: the PPI for intermediate goods, the wage rate for pharmaceutical workers, hospital prices, marketing expenditures on non-H₂ drugs, the number of firms in the market, a GERD approval dummy variable, a time trend, and a constant. The next section reports the results of estimating the model.

¹²Non-ulcer drug products refers to all products that are not H₂-receptor antagonists and may include other ulcer drugs that work through different mechanisms.

¹³The number of firms with close, competing, non-H₂-receptor antagonist drugs (Carafate, Cytotec, and Prilosec) was also considered, but its coefficient was not significant in the first-stage instrumental variable regressions.

2.5 Marketing's Effects

This section and the next report the central empirical findings on the competitive effects of the substantial resources that pharmaceutical companies devote to their marketing efforts. The basic results, parameter estimates, and elasticities from the marketing model are discussed in this section while the following section explores, through a series of simulations, how marketing's effect on product differentiation and competition changed over time in the ulcer drug market. These results suggest that both a firm's own marketing and that of its competitors factored significantly in the demand for its product and the elasticities of that demand, and that total marketing by all firms appeared to reduce the degree of product differentiation in the market.

2.5.1 Estimation Results

Since the estimated equation involves a regression of share ratios, $\ln(s_j) - \ln(s_0)$, on product characteristics, the effect of the estimated coefficients on demand is not immediately obvious. The interpretation of coefficients is straightforward, however, if one considers their effect on marginal utility in equation 2.1.

Turning to the results of the model in the first column of Table 2.4, one first notices that both the coefficients own marketing, M_j , and others' (competitors') marketing, M_{-j} , are significant and have the expected signs. The firm's own marketing efforts increase the valuation of its product while the marketing efforts of its competitors detract from it. The coefficient on price is also significant and negative, as one would expect. The other characteristics, which here act as control variables, are significant and conform to our expectations, with the possible exception of dosage frequency.¹⁴ The number of

¹⁴The positive frequency coefficient may arise from the confounding of two competing effects in the data: a negative value resulting from the initial requirement of multiple daily doses of Tagamet and a positive effect from Tagamet's initial monopoly. Tagamet was originally administered four times a day. Shortly after Zantac entered, however, Zantac and then Tagamet moved to a single daily dosage which all subsequent entrants also adopted. The frequency variable thus also acts as a dummy variable for early in the sample.

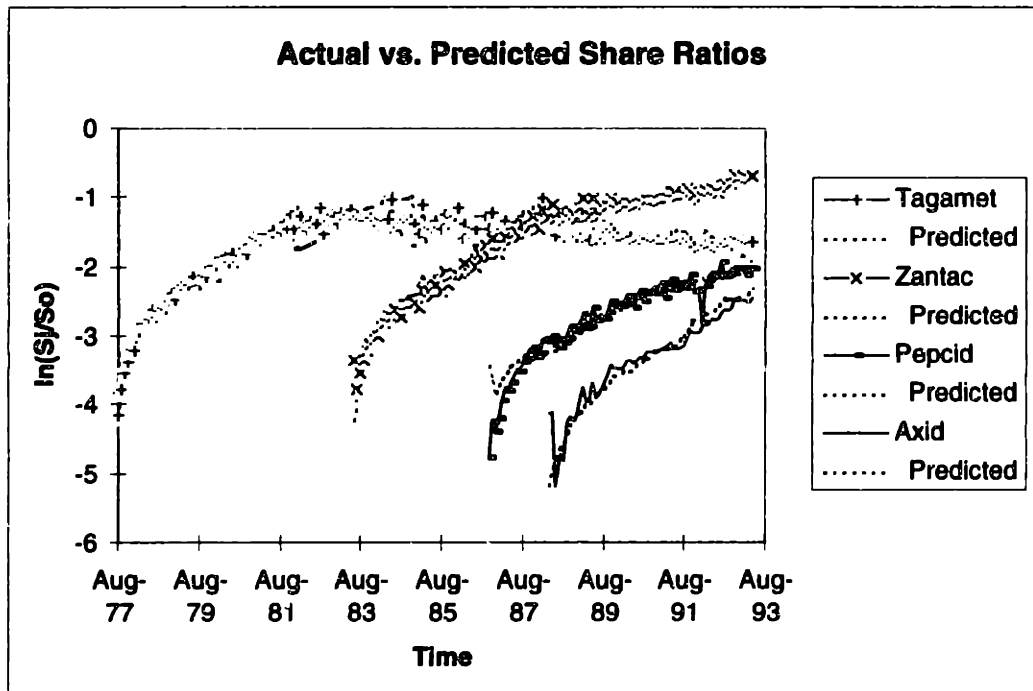


Figure 2-4: Actual versus Predicted Share Ratios

indications for which the drug has been approved and time on the market yield positive utility. Increasing the number of adverse drug interactions decreases utility. The graph of the predicted and actual shares of the model is given in Figure 2-4 does not reveal any systematic pattern among the errors.

The general method of moments estimation used corrects for the first order serial correlation of the errors observed in the data. A caveat should be given, however, with respect to the standard errors reported in Table 2.4. The estimated depreciation rate is determined by minimizing the sum of the squared residuals from the regression equation and is assumed to be known with certainty. The error in its estimation has not been included, due to the computational burden, in the reported standard errors, which therefore are underestimated.

The most intriguing finding concerns the effect of total marketing on product differ-

$\ln(\text{Share}_j/\text{Share}_0)$	GMM*		OLS		2SLS	
Monthly Depreciation Rate	4.6%		4.2%		2.8%	
Total Ads	0.106	(0.041)				
Own Marketing	5.474	(0.400)	4.343	(0.164)	2.839	(0.228)
Others' Marketing	-1.515	(0.322)	-0.998	(0.091)	-0.677	(0.118)
Price	-1.634	(0.420)	-0.435	(0.122)	-0.074	(0.296)
Constant	-3.858	(0.528)	-4.422	(0.145)	-4.654	(0.321)
Age	0.019	(0.002)	0.012	(0.001)	0.010	(0.003)
Frequency	0.359	(0.053)	0.333	(0.020)	0.363	(0.034)
Interactions	-0.090	(0.016)	-0.040	(0.007)	-0.014	(0.017)
Indications	0.117	(0.028)	0.116	(0.020)	0.097	(0.031)
Zantac	1.244	(0.217)	0.660	(0.092)	0.684	(0.168)
Pepcid	1.847	(0.195)	1.432	(0.130)	1.353	(0.247)
Axid	0.901	(0.217)	0.806	(0.150)	0.762	(0.293)
R²	0.933		0.950		0.948	

* Corrected for first order serial correlation.

Table 2.4: Discrete Choice Model with Marketing. (Standard errors are in parentheses. N = 449 observations.)

entiation. Recall that the scale parameter was parameterized as

$$\sigma = (1 + \gamma(\text{TotalMarketing}))^2 \quad (2.10)$$

and that the ratio of the market shares for product j and product k is

$$\ln \left(\frac{s_j}{s_k} \right) = \frac{\delta_j - \delta_k}{\sigma}. \quad (2.11)$$

The results of the GMM estimation give a positive and significant estimate for γ of 0.106. Thus total marketing apparently decreased the amount of product differentiation in the ulcer drug market. Since the stock of total marketing ranged from zero to 1.89, this implies that $1/\sigma$ varied from 1 to 0.69, roughly a 30% change in the scale of product differentiation over the period of the sample, and most of this change occurred in the second half of the sample period.

There are a number of possible explanations for this observed change in the scale of product differentiation over the course of the sample, but marketing appears to be the most plausible one once the other factors are ruled out. Since marketing stocks are highly correlated with both sales and time due to the small, estimated depreciation rate, several alternate specifications of σ were considered, including adding a time trend or cumulative sales as linear terms in equation 2.7 and expressing σ as a series of dummy variables for the number of firms in the market. In each case, the alternate specifications produced either insignificant or inconsistent results.¹⁵ For this reason, the specification with σ as a function of total marketing is preferred.

For purposes of comparison with previous studies, the estimates from a simple logit

¹⁵Cumulative sales might be considered as a proxy for experience, but parameterizing σ as a function of cumulative sales gave a coefficient on sales was not significant. Adding both total marketing and a time trend to σ lead to a near zero depreciation rate. Using a series of dummy variables for the number of firms in the market in the expression for σ produced insignificant coefficients on each of the dummy variables suggesting that market structure alone may not be the primary cause of the observed change in the scale of product differentiation. Finally, when a linear, rather than a squared, parameterization was used, σ tended to become negative for specifications other than total marketing.

model are presented in the first columns where the model was estimated by ordinary least squares (OLS) and two-stage least squares (2SLS). In the standard logit model, the idiosyncratic components of consumer preferences are assumed to be constant, $\sigma = 1$ in equation 2.6, and, in particular, is not influenced by firms' marketing efforts. One advantage of presenting the OLS results is that the effectiveness of the instrumental variables in controlling for the endogeneity of price and advertising can be explored in a simple framework by comparing them with the 2SLS parameter estimates in Table 2.4.¹⁶ All variables were significant in the first-stage regressions of price and marketing on the instrumental variables. In the marketing regression, however, the coefficient on non-H₂ marketing was negative, which is a potential concern.¹⁷ Adding instrumental variables to correct for endogeneity preserves the signs of all parameters, but the coefficient on price becomes smaller in magnitude and is no longer significant. The coefficients for own and competitors' advertising also decrease in the 2SLS results, but this may be attributed to the different optimal depreciation rates found in the OLS and 2SLS regressions since capital stocks of advertising will be significantly larger if depreciated at the 2SLS rate of 2.8% than at the higher OLS rate of 4.2%. Figure 2-5 graphs the evolution of marketing stocks for each of the four ulcer drugs depreciated at 4.6% per month, the estimated depreciation rate for the full marketing model.

Finally, the first row of Table 2.4 reports the estimated depreciation rates for each specification. The estimated depreciation rate for marketing ranges from a low of 2.8% per month, roughly 20% per year, for the 2SLS regression to a high of 4.6% per month or about 40% annually for the full model. These depreciation rates accord with those generally found in consumer marketing studies (Berndt 1991). Figure 2-5 graphs the

¹⁶Note that the marginal utilities are not directly comparable since the values for σ will differ.

¹⁷Suppose a firm receives good news about its ulcer drug and decides to increase its marketing efforts in order to capitalize on the event. If the total marketing budget for the firm is fixed in advance, an increase in the marketing expenditures for the ulcer drug can only occur if spending on other products is reduced. This introduces a negative correlation between the error term of the regression equation and the instrumental variable, invalidating its use as a valid instrument.

A preliminary check suggests that removing non-H₂ marketing as an instrumental variable may reduce the size and the significance of the estimated price coefficient but further work is required.

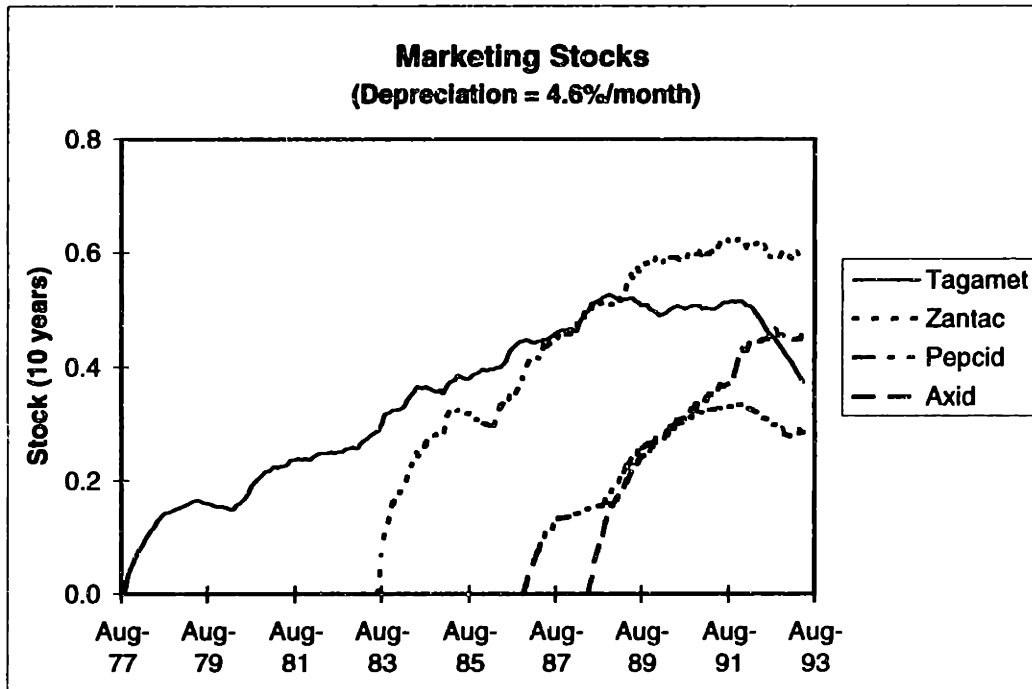


Figure 2-5: Marketing Stocks (depreciated at 4.6% per month)

evolution of marketing stocks for each of the four drugs for the marketing model where $\sigma = \sigma(M_{tot})$ and the estimated depreciation rate is 4.6% per month.

2.5.2 Elasticities

How marketing affects the elasticities of demand is important for understanding product competition in the ulcer drug market. In this section, the elasticities of quantity demanded with respect to price and marketing are derived together with the response of the price elasticity of demand to an increase in marketing. To the extent that marketing succeeds in differentiating products, one would expect that a firm's marketing would make the demand for its product more inelastic. The effect of marketing by all the firms also appears in these elasticities, each of which is divided by $\sigma(M_{tot})$.

To calculate the elasticities, recall that the market share, s_j , in equation 2.4 is the probability of choosing product j . The demand, q_j , for product j is then just the product

of its market share, s_j , times the size of total market, Q , or $q_j = Qs_j$. Thus the elasticity of demand for product j with respect to its own price is

$$\eta_{p_j} = \frac{\partial \ln(q_j)}{\partial \ln(p_j)} = -\frac{\alpha p_j}{\sigma} (1 - s_j), \quad (2.12)$$

where α is the coefficient on price in equation 2.1. Similarly, the elasticity of demand for product j with respect to the price charged by competitor k is

$$\eta_{p_k} = \frac{\partial \ln(q_j)}{\partial \ln(p_k)} = \left(\frac{\alpha p_k}{\sigma}\right) s_k. \quad (2.13)$$

The elasticities of demand with respect to marketing can also be computed. The elasticity of the demand for product j with respect to own marketing, M_j , is

$$\eta_{M_j} = \frac{\partial \ln(q_j)}{\partial \ln(M_j)} = \frac{(\beta_{M_j} - \beta_{M_{-j}}) (1 - s_j) M_j}{\sigma (M_{tot})}, \quad (2.14)$$

where β_{M_j} is the coefficient on product j 's own marketing effort and $\beta_{M_{-j}}$ is the coefficient on marketing by its competitors. A similar equation holds for the elasticity of demand with respect to marketing by one of its competitors, k ,

$$\eta_{M_k} = \frac{\partial \ln(q_j)}{\partial \ln(M_k)} = -\frac{(\beta_{M_j} - \beta_{M_{-j}}) s_k M_k}{\sigma (M_{tot})}. \quad (2.15)$$

Finally, one can evaluate the degree to which a firm's marketing increases its market power by reducing the price elasticity of demand for its product and enabling it to raise prices. Taking the partial derivative of equation 2.12 for η_{p_j} with respect to firm j 's marketing and converting it to an elasticity yields

$$\mu_j = \frac{\partial \ln(\eta_{p_j})}{\partial \ln(M_j)} = -\frac{M_j}{\sigma (M_{tot})} [(\beta_{M_j} - \beta_{M_{-j}}) s_j + 2\gamma (1 + \gamma M_{tot})]. \quad (2.16)$$

For $\gamma > 0$ and $(\beta_{M_j} - \beta_{M_{-j}}) > 0$, as is the case for the model estimates in the first column of Table 2.4, this implies that increasing firm j 's advertising reduces the price elasticity

of its demand. Holding other variables fixed, an increase in total marketing reduces the effectiveness of a single firm's advertising in lowering its elasticity of demand. Marketing also has a greater effect on the price elasticity for firms with larger market shares.

Using equations 2.12 through 2.15, estimates for the elasticities of demand with respect to price and marketing can be computed from the parameter estimates in Table 2.4. These elasticities are calculated for the last period of the sample, May 1993, and are presented in Table 2.5. Demand is more sensitive to one's own than another's price, as expected. The own price elasticities for the four H₂-receptor antagonist drugs range from -1.52 (Tagamet) to -1.83 (Axid). The cross-price elasticities are positive and smaller, ranging from 0.09 to 0.55. Thus, a 10% increase in Tagamet's price would lead to a 15% decline in quantity sold while a 10% increase in the price of Zantac, its closest competitor, would only increase the quantity of Tagamet sold by less than 6%. These elasticities accord with those obtained by Ellison, Cockburn, Griliches, and Hausman (1994)¹⁸, who obtained their results for the anti-infective therapeutic market, and Stern (1994), who studied four different therapeutic markets.

Similarly, demand responds more to one's own marketing efforts than those of a competitor. The demand elasticities with respect to own marketing stocks fall between 2.18 (Zantac and Axid) and 1.33 (Pepcid). The elasticities with respect to the total marketing of one's competitors advertising are again smaller and of opposite sign from -0.10 (Pepcid and Axid) to -0.77 (Zantac).

2.6 Simulations

To illustrate the evolving nature of competition in the ulcer drug market during this period, three simulations were calculated: the effect of a firm's marketing on its own elasticity of demand, the effect of an increase in marketing on market expansion and business stealing from the firm's competitors, and the change in cost of entry over time.

¹⁸The own price elasticities they estimated for branded cephalosporins ranged from -0.4 to -1.94 while the cross-price elasticities were between -0.68 and 0.72.

Elasticities (May 1993)

	Quantity							
	Tagamet		Zantac		Pepcid		Axid	
Tagamet Price	-1.52	(0.45)	0.17	(0.05)	0.17	(0.05)	0.17	(0.05)
Zantac Price	0.55	(0.16)	-1.57	(0.47)	0.55	(0.16)	0.55	(0.16)
Pepcid Price	0.12	(0.03)	0.12	(0.03)	-1.55	(0.46)	0.12	(0.03)
Axid Price	0.09	(0.03)	0.09	(0.03)	0.09	(0.03)	-1.83	(0.54)
Tagamet Marketing	1.68	(0.11)	-0.19	(0.01)	-0.19	(0.01)	-0.19	(0.01)
Zantac Marketing	-0.77	(0.05)	2.18	(0.14)	-0.77	(0.05)	-0.77	(0.05)
Pepcid Marketing	-0.10	(0.01)	-0.10	(0.01)	1.33	(0.08)	-0.10	(0.01)
Axid Marketing	-0.10	(0.01)	-0.10	(0.01)	-0.10	(0.01)	2.17	(0.14)

Table 2.5: Elasticities of Demand With Respect to Price and Marketing.

These simulations are not meant to be taken literally and must be interpreted with care. But they do provide a useful means to assess the practical import of the estimated parameters of the model. The most obvious limitation of the simulations is that they do not account for potential competitive responses to the hypothesized changes in the simulation. Nor do they separate out the effect of the changing size of the potential market, which grew at the rate of the U. S. population over the course of the sample, some 17.3% from 1977 to 1993 or about 1.0% per year during this period. And, of course, the models themselves are subject to the limitation that they include only a few explanatory variables and ignore others, such as the business cycle and changes in physician practices and training, whose effects may have differed at different times over those 17 years.

The results of these simulations are discussed next.

2.6.1 Marketing's Effect on Price Elasticity

Using the formula in equation 2.16, one can compute in terms of an elasticity measure how the price elasticity of demand for a particular drug responds to an increase in its marketing, which also increases total marketing. Evaluating the marketing elasticities, μ_j , of the price elasticity of demand for the four ulcer drugs at the end of the sample reveals that marketing was most effective in reducing the elasticity of demand for Zantac, the market leader with $\mu_{Zantac} = -0.874$, followed by Tagamet, $\mu_{Tagamet} = -0.256$, Axid, $\mu_{Axid} = -0.184$, and Pepcid, $\mu_{Pepcid} = -0.150$.

How the advertising affects the price elasticity of demand over time in this market is also of interest. Figure 2-6 shows the effect of marketing on the price elasticity of demand for Tagamet over the sample period. The dashed lines represent confidence intervals of two standard deviations. Initially, as Tagamet increased its stock of marketing, marketing became increasingly effective in differentiating Tagamet from other ulcer remedies and making demand more inelastic. This trend continued until Zantac first entered the market, triggering strong competition in marketing between Tagamet and Zantac. During

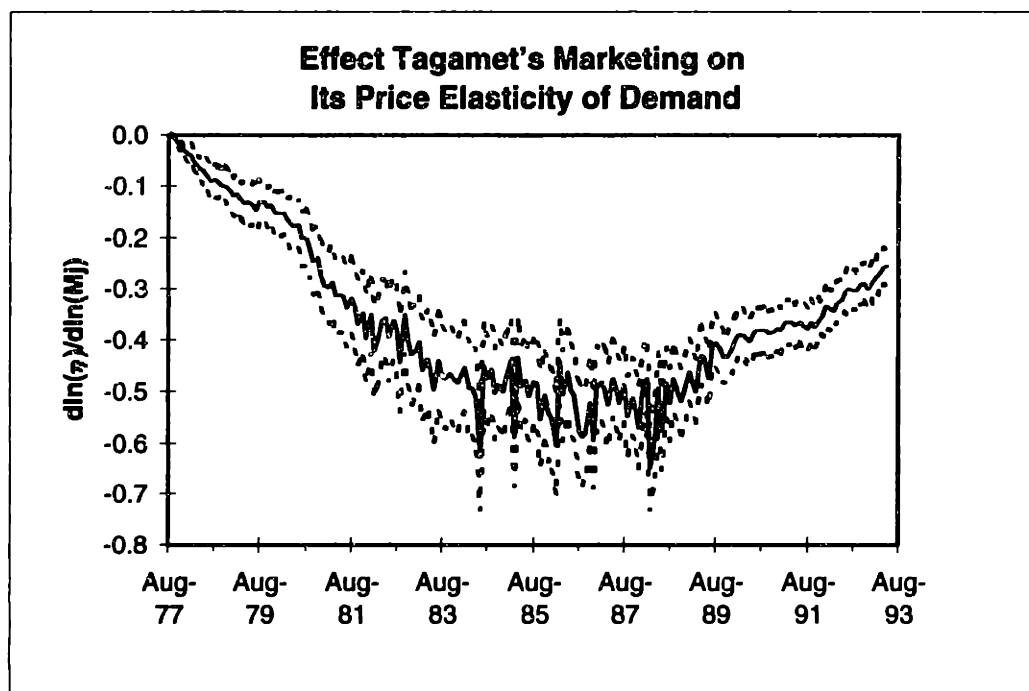


Figure 2-6: Effect of a 5% Increase Tagamet's Marketing Stock on Its Price Elasticity of Demand

the next few years, Pepcid and Axid also entered, and the effect of Tagamet's marketing on its price elasticity of demand remained high but no longer increased. Toward the end of the sample, Tagamet's marketing stock remained constant, before declining sharply at the end of the sample, while its competitors continued to increase their marketing efforts. Tagamet lost market share, and the responsiveness of its price elasticity of demand to marketing declined. The change in magnitude of $\mu_{Tagamet}$ during this period is substantial. In the middle of the sample, marketing is roughly two to three times as effective in decreasing Tagamet's price elasticity than either early or late in the market.

2.6.2 Business Stealing versus Market Expansion

Another way to illustrate marketing's effect is to examine the change in Tagamet's market share that would result from a hypothetical fixed increase in its marketing efforts. This

analysis is complicated, however, by the changing market structure: Tagamet begins as a monopoly and ends as part of a four firm oligopoly. In an attempt to alleviate potential problems created by comparisons across different market structures, these experiments are conducted within periods when the market structure remains unchanged. For each such period, the results of increasing Tagamet's marketing efforts are computed for a date seven months after the arrival of the most recent entrant and seven months before the arrival of the next. Seven months was chosen to avoid the complications of heavy promotions on entry by new firms and prior to entry by incumbents.

The model offers some insights on the long-standing debate over whether the effect of marketing efforts is primarily business stealing or market expansion. To evaluate the relative importance of these two effects in this market, consider the marginal effect of a five percent increase in Tagamet's marketing stock. Since Tagamet enjoyed a monopoly in the early part of the sample period, Tagamet's marketing efforts during this time were by definition entirely market expanding. With the entry of Zantac, both companies attacked each other's claims of relative merits. Zantac had fewer adverse drug interactions than Tagamet, and, at first, Zantac employed a twice a day dosage while Tagamet had to be taken four times daily. A year and a half later, Tagamet converted to twice per day and then once a day. During this period, and subsequently with the entry of Pepcid and Axid, these drug manufacturers competed aggressively through their marketing efforts, which had both rivalrous and market expanding components.

As shown in Figure 2-7, early on, Tagamet's marketing efforts worked almost entirely through expanding the market. But as others introduced competing drugs and marketing competition increased, marketing's effectiveness in creating new demand plummeted until by the end of the sample roughly half of the new customers recruited through Tagamet's marketing came from its competitors. Not only was Tagamet's marketing now less effective in gaining market share, much of that share came from its competitors rather than from an increase in the size of the overall market for ulcer drugs.

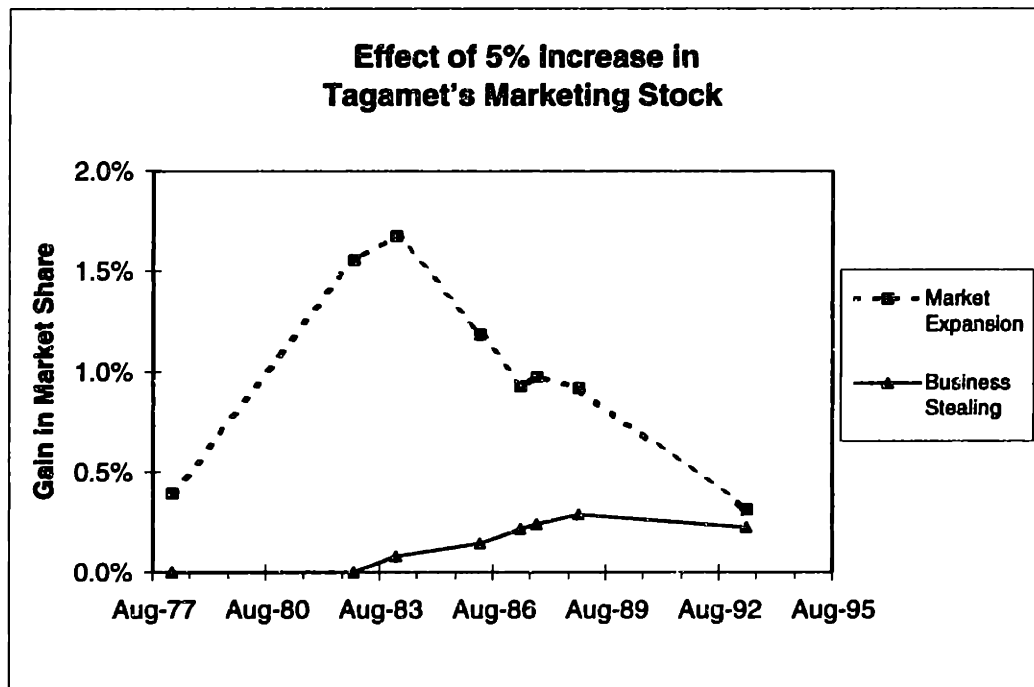


Figure 2-7: Business Stealing versus Market Expansion: Effect of a 5% Increase in Tagamet's Marketing Stock on Market Share

2.6.3 Marketing and Cost of Entry

Twenty years ago, Bond and Lean (1977) argued that the marketing and promotional efforts convey considerable advantages to pioneering pharmaceutical firms. To convince physicians to switch from an existing drug to a new one, they conjectured, requires that later entrants either offer a lower price, promote more heavily, or both. Berndt, Bui, Lucking-Reiley, and Urban (1997) found two sources of support for this conjecture in the ulcer market. Cumulative marketing-to-sales ratios for any time period are always lowest for the pioneer, Tagamet, and increase successively for each subsequent entrant suggesting that later entrants must invest more in marketing to overcome incumbents' advantages. They also find substantial effects arising from order of entry in their regression models.

There are several ways in which marketing deters entry in the model considered here. First, by raising the valuation of an existing drug, marketing raises the valuation an entrant must achieve in order to acquire a given market share. Since most of drugs' physical characteristics – interactions, indications, etc. – depend on the chemical and biological properties of a particular molecule, they are largely fixed and immutable. To alter the valuation of a particular drug, therefore, the firm must resort to the strategic instruments of pricing and marketing rather than altering its physical characteristics. But, if all firms increase their marketing, this both makes entry more difficult and may force existing firms into closer competition, as seems to be the case in the market for ulcer drugs. Finally, in this market, the cumulative stock of advertising appears to reduce the degree of product differentiation making it more difficult for a potential entrant to achieve a given degree of separation from other products without investing more in marketing or lowering its price.

Taken together, these effects of marketing raise the cost of entry to potential entrants. One way to measure this is to calculate the amount of marketing an entrant with a given set of product characteristics would have to undertake to achieve a given market share. How this amount changes over time would then provide one indication of the changing costs of entry. Consider, for example, a hypothetical entrant with price and

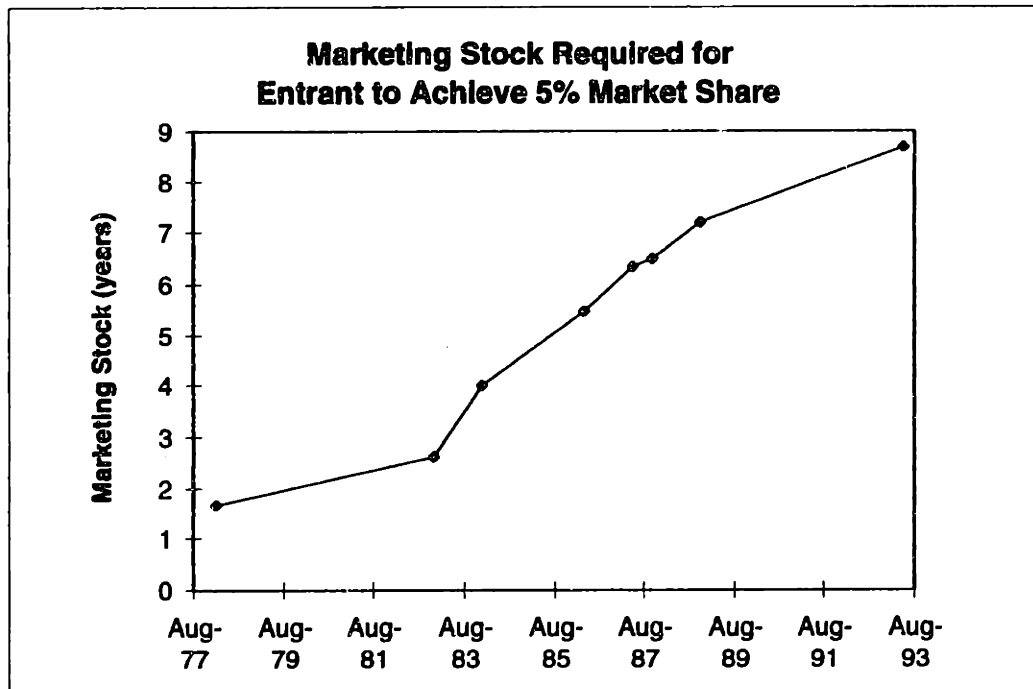


Figure 2-8: Marketing Stock Required for Hypothetical Entrant to Achieve a 5% Market Share

drug characteristics equal to the mean characteristics of all the drugs then in the market and calculate the stock of marketing required to achieve a 5% market share. Again to moderate the possible confounding effects of changes in the market structure, choose pairs of times, one early, one late, within periods when the number of competing firms is constant. Figure 2-8 presents the results of these calculations. This graph shows that the marketing costs of entry for the hypothetical entrant increased roughly fourfold over the sample period.

2.7 Conclusion

Economists have long been interested in how product differentiation affects market competition and how product differentiation changes over time within markets, but economists have been hampered by the lack of adequate, tractable models in tackling these

empirically difficult issues. To address these and related questions, this chapter developed a variant of the discrete choice model that incorporates the effects of marketing by the firm and its competitors and that allows marketing to affect the scale of product differentiation. The model enables the estimation of hard-to-measure effects of marketing using routine econometric methods while avoiding the sophisticated but computationally intensive numerical techniques of the related random coefficients models of Berry (1994) and Berry, Levinsohn, and Pakes (1995).

Using a panel of monthly data from 1979 to 1993, the model was estimated for the ulcer drug market, which leads to several findings. Marketing played a central role in the market for ulcer drugs during this period. A firm's own marketing increased the average valuation of, and hence the demand for, its drug, although the marketing efforts of its competitors reduced its valuation and demand. A firm's marketing also made its demand more inelastic while the total marketing by all firms appeared to decrease the degree of product differentiation. Over time, marketing became increasingly rivalrous as marketing efforts were less effective in creating new demand but more successful in stealing business from rival firms. Finally, marketing raised the cost of entry to potential new competitors.

Chapter 3

Empirical Evidence of Market Power and Dynamic Pricing in the Cigarette Industry

3.1 Introduction

Previous empirical studies have found that the price elasticity of demand for cigarettes is significantly higher for new smokers than for older smokers (Lewit, Coate, and Grossman (1981), and Lewit and Coate (1982)). Cigarette firms thus face a total demand composed of two distinct segments: highly elastic younger smokers and highly inelastic older smokers. Competitive firms produce to equate price to marginal cost, but firms with market power will account for the ratio of young to old smokers in setting their prices because of their different elasticities. In addition, if firms are forward-looking, their prices will also reflect the current number of nonsmoking children who are tomorrow's potential young smokers. This chapter exploits these unique aspects of cigarette demand to test for market power and dynamic pricing in the cigarette industry using these basic intuitions.

Most cigarette smokers take up smoking in their teens and early twenties. Those who do not start during these years rarely do later (*see, e.g.*, studies reviewed in U.S.

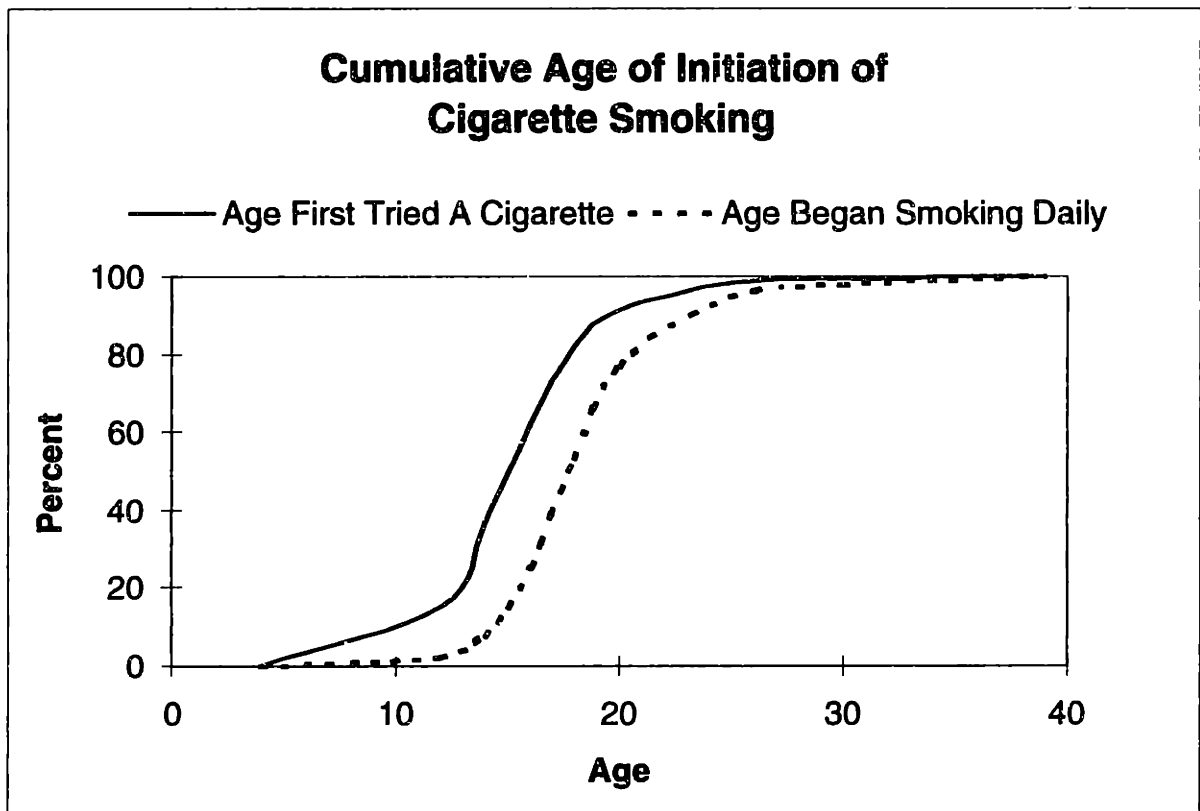


Figure 3-1: Cumulative Age of Initiation of Cigarette Smoking Among Persons Aged 30–39 Years Who Have Ever Smoked Daily, United States 1991; National Household Survey on Drug Abuse (CDC).

Department of Health and Human Services (1994)). Almost all first use has occurred by the time people graduate from high school and almost all regular smoking by the end of college. This is shown in Figure 3-1, which presents the cumulative age of initiation of cigarette smoking among persons aged 30 to 39 years who ever smoked daily (National Household Survey on Drug Abuse 1991). Since the nicotine delivered in cigarette smoke can be highly addictive, the quit rate among smokers is very low.¹

The market for cigarettes in the United States historically has been highly concentrated. Although served by six major domestic suppliers, just two, Philip Morris and

¹Each year, nearly 20 million people try to quit smoking in the United States (U.S. Department of Health and Human Services 1990), but only about 3 percent achieve long-term success (U.S. Department of Health and Human Services 1994).

R.J. Reynolds, dominated the market during the period studied. Together Philip Morris and R.J. Reynolds controlled nearly 73% of the unit volume produced in 1993 (Maxwell 1994). Cigarettes are a highly profitable, highly differentiated product with strong brand loyalties, less than 10 percent of smokers ever switch brands (Pollay, Siddarth, and Siegel 1996).²

Numerous studies have examined the demand for cigarettes (*see* U.S. Department of Health and Human Services (1994) for a cogent summary). Lewit, Coate, and Grossman (1981) studied a panel data set of teenagers from 1966 to 1970 and found that, unlike adults, teenager cigarette demand and smoking initiation rates responded sharply to changes in cigarette prices (elasticities of -1.4 and -1.2, respectively). In comparison, Lewit and Coate (1982), in a cross section of 1976 data, estimated the adult price elasticity of demand at -0.42. They found that the price elasticity for smoking participation (-0.26) exceeds that for cigarette demand (-0.10) and that the decision to begin smoking for young adults, particularly males, is price elastic. This led them to conclude, in light of their earlier work with Grossman, that higher cigarette prices “appear to affect cigarette demand by affecting the decision to smoke or not rather than by causing existing smokers to reduce the amount of cigarettes they smoke.” (p. 136).

3.2 Theoretical Models

Both static and dynamic models of firm behavior predict that firms with market power will adjust their prices according to the ratio of young to old smokers. The principal difference between the static and dynamic models appears in the effect that younger children have on the pricing decision of the firm. For the forward-looking or dynamic firm, if there are large numbers of younger children in the population today, the firm has an incentive next period (when these children become teenagers) to reduce its price to attract them as new smokers. Thus the firm has less to gain from recruiting new smokers

²Smokers are extremely brand loyal despite their inability to distinguish brands in blind tests as demonstrated as early as 1920 by J. Walter Thomson.

this period, and prices will be higher in the current period. A second distinction between the static and dynamic models arises in their treatment of the age composition of older smokers. In the static model, firms care only about the total number of older smokers; the relative proportion of middle-aged to elder smokers among these older smokers does not affect prices. This is not true in a dynamic setting where the ratio of middle-aged to elder smokers can affect the pricing decision.

The next two subsections derive first a two firm, static model of Bertrand competition with differentiated products and then a single firm, stochastic dynamic model of the firm's cigarette pricing strategy.

3.2.1 Bertrand Competition with Differentiated Products

Consider two competing firms, i and j , whose products are imperfect substitutes and who face two types of consumers: young, $k = 1$, and old, $k = 2$. Younger consumers have a more elastic demand than the old. Demand is the product of the number of consumers, n_k , times the demand per consumer, which, for simplicity, is assumed to be linear in prices. If firms i and j charge prices p_i and p_j , the demands for firm i from young and old smokers, respectively, are:

$$q_{1i} = n_1 (a_1 - b_1 p_i + c_1 p_j) \text{ and} \tag{3.1}$$

$$q_{2i} = n_2 (a_2 - b_2 p_i + c_2 p_j), \tag{3.2}$$

where $a_k, b_k, c_k > 0$ and $b_k > c_k$ for $k = 1, 2$.

In this representation, the ratio of c_k to b_k is a measure of the degree of product differentiation in the market. The more highly differentiated the products, the closer c_k moves toward zero. The assumption that $b_k > c_k$ ensures that demand for a given brand is more sensitive to a change in its own price than a change in its competitor's price.

Combining equations 3.1 and 3.2, the total demand for firm i is

$$\begin{aligned} Q_i(p_i, p_j) &= (a_1 n_1 + a_2 n_2) - (b_1 n_1 + b_2 n_2)p_i + (c_1 n_1 + c_2 n_2)p_j \\ &= \alpha - \beta p_i + \gamma p_j. \end{aligned} \quad (3.3)$$

To solve for the Bertrand Nash equilibrium, first compute the price firm i would set taking p_j as given by solving

$$\max_{p_i} \pi_i(p_i, p_j) = (p_i - c)(\alpha - \beta p_i + \gamma p_j), \quad (3.4)$$

where the firm has constant marginal costs, c . From the first order condition, firm i 's reaction function, $p_i^*(p_j)$, is

$$p_i^*(p_j) = R(p_j) = \frac{\alpha + \gamma p_j + \beta c}{2\beta}. \quad (3.5)$$

The symmetric Bertrand Nash equilibrium strategies for the firms are then

$$\begin{aligned} p_i^{NE} &= p_j^{NE} = \frac{\alpha + \beta c}{2\beta - \gamma} \\ &= \frac{(a_1 n_1 + a_2 n_2) + (b_1 n_1 + b_2 n_2)c}{2(b_1 n_1 + b_2 n_2) - (c_1 n_1 + c_2 n_2)}, \end{aligned} \quad (3.6)$$

and the equilibrium profits are

$$\pi_i^{NE} = \left[\frac{(\alpha + (\gamma - \beta)c)}{(2\beta - \gamma)} \right]^2 \beta. \quad (3.7)$$

These strategies are strategic complements.

Clearly the prices firms choose depend on the relative number of young and old smokers in the population. For parameter values corresponding to the observed elasticities, the equilibrium price, p_i^{NE} , is an increasing function of the number of young, n_1 , and a decreasing function of the number of old, n_2 , as shown in the Appendix. In order

to obtain a crude estimate of the expected size of the effect from changing the relative proportions of young and old in the population, equation 3.6 is reexpressed in terms of the ratio of young to old smokers, $r = n_1/n_2$, and differentiated to give

$$\frac{dp_i^{NE}}{dr} = \frac{2a_1b_2 - 2a_2b_1 + a_2c_1 - a_1c_2 + (b_2c_1 - b_1c_2)c}{((c_1 - 2b_1)r - 2b_2 + c_2)^2}. \quad (3.8)$$

The predicted magnitude of $\frac{dp_i^{NE}}{dr}$ is of particular interest since it can be compared with empirical estimates. By constraining the elasticities of demand to equal those observed and substituting the mean value for the ratio of young to old from the state panel data described below, one can derive values for the underlying parameters of the model and the predicted value of the derivative, $\frac{dp_i^{NE}}{dr}$, of the equilibrium price with respect to the ratio of young to old. These values, obtained through a nonlinear search procedure, are presented in Table 3.1. The top panel contains the predictions of the model based on the assumed values for the model parameters listed in the lower panel. The elasticities of demand for young and old, η_1 and η_2 , are from Lewit, Coate, and Grossman (1981) and Lewit and Coate (1982); the ratio, r , of young to old equals 0.41 at the mean of state panel data used in estimations in the second half of this chapter; and the marginal cost, c , of a pack of cigarettes comes from Keeler, Hu, Barnett, and Manning (1993).

Predicted values are calculated under a number of different scenarios to analyze the sensitivity of the predictions to changes in model parameters. Using the mean values from the state panel data, the model predicts a value for the derivative of -0.29, an equilibrium price of 129 cents, and a markup, $(price - c)/price$, of 77%. For comparison, the mean real price of cigarettes in the sample is somewhat lower at 85.6 cents. The next three columns of the table calculate predictions assuming that the elasticities are 30% greater than those observed (more elastic) and for values of r one standard deviation less than the mean (more old) and one standard deviation greater than the mean (more young). These numerical experiments suggest that the regression coefficient on r would be of order -0.3 based on a model of two firms with differentiated products competing à

		Sample Mean	More Elastic	More Old	More Young
Theoretical	$\frac{dp_i^{NE}}{dr}$	-0.29	-0.22	-0.37	-0.23
Predictions	p_i^{NE}	129	78	140	120
	Markup	77%	62%	79%	75%
	η_1	-1.40	-1.82	-1.40	-1.40
Assumed	η_2	-0.42	-0.55	-0.42	-0.42
Values	r	0.41	0.41	0.35	0.46
	c	30	30	30	30

Table 3.1: Bertrand Model Predictions

la Bertrand.

3.2.2 Stochastic Dynamic Model

To obtain an estimate for the expected change in price resulting from a change in the proportion of middle-aged to older smokers, a second model incorporating the dynamic effects of current pricing on future demand is developed. The details of the dynamic stochastic programming model of single firm with market power are given in the Appendix. The model is solved numerically using parameter values derived from the literature. As in the static case, the firm in the dynamic model lowers prices when the ratio of young smokers to older smokers increases. In addition, the model gives an estimate for the effect on price of changing the ratio of middle-aged to senior assuming that they both have the same elasticity. The size of the predicted effect is quite low, between 0 and 0.05, although given the number of assumptions required for this nonlinear model, this estimate must be regarded as an order-of-magnitude estimate at best.

3.3 Empirical Tests

The theoretical models developed above suggest several empirical tests for market power and dynamic pricing effects. Evidence that cigarette prices are a function of the age distribution constitutes evidence that the market is not perfectly competitive and that firms possess market power. Because young and old smokers have different price elasticities of demand for cigarettes, firms with market power will charge lower prices when the ratio of young to old is higher. This provides a test of the market power hypothesis that applies whether firms optimize dynamically or not.

To determine whether firms maximize profits dynamically, consider two additional tests. The first examines the effect on price of the number of non-smoking, younger children in the population. The number of children is irrelevant to the static firm, which sets price to maximize its current profits, but does matter to the dynamic firm, which

maximizes the present discounted value of its profit stream.

A second test for dynamic pricing effects is whether the age composition of adult smokers affects prices. Assume, for the moment, that all adult smokers have the same elasticity of demand. For the single period, profit maximizing firm, only the total number of adult smokers in the population matters. Whether these smokers are middle-aged or senior citizens does not affect its calculation of current profits since both groups have the same price elasticity of demand. This is not true for the forward-looking, or dynamic, firm. In this case, the relative number of middle-aged and senior smokers does affect the present value of the firm's discounted profits as the firm balances the benefits of higher profits resulting from higher prices today against the need to recruit new smokers through lower prices in the future. However, this second test suffers from its limited ability to discriminate between dynamic effects and differences in price elasticities between middle-aged and senior smokers, as discussed further in the results section.

Two data series are used to test for market power and dynamic pricing in the cigarette industry: 1) a state panel from 1975 to 1989 and 2) a national time series from 1950 to 1993. Table 3.2 provides an overview of cigarette prices and taxes per pack from 1975 to 1989. The empirical analysis focuses on the relationship between cigarette prices and the age distribution of the population while controlling for other factors affecting demand, such as personal income, or supply, such as input and production costs.

Since the number of smokers by age and state is not available, the regressions use ratios of the actual population, including both smokers and nonsmokers, for the ratio of young to old smokers and the ratio of senior to middle-aged. To the extent that the relative percentages of smokers in the various age cohorts for a given year changes over time, this will introduce measurement error in the regressors, but since the variables are ratios, an overall decline in smoking prevalence that is the same for all age groups will not. The limited data that are available indicate that the largest change in national smoking prevalence among age groups occurred from 1955 to 1965, which may affect the results for the 1950 to 1993 national time series, although the measurement error problem

Year	Average state tax (cents)	Average federal tax (cents)	Average cigarette price (cents)	Taxes as percent- age of average price¹	Real² average state tax (cents)	Real² average federal tax (cents)	Real² average cigarette price (cents)
1975	12.2	8.0	44.5	44.5	22.7	14.9	82.7
1976	12.4	8.0	47.9	41.4	21.8	14.1	84.2
1977	12.5	8.0	49.2	40.5	20.6	13.2	81.2
1978	12.9	8.0	54.3	37.1	19.8	12.3	83.3
1979	12.9	8.0	56.8	35.5	17.8	11.0	78.2
1980	13.1	8.0	60.0	34.5	15.9	9.7	72.8
1981	13.2	8.0	63.0	33.1	14.5	8.8	69.3
1982	13.5	8.0	69.7	29.9	14.0	8.3	72.2
1983	14.7	12.0	81.9	26.8	14.8	12.0	82.2
1984	15.3	16.0	94.7	33.2	14.7	15.4	91.1
1985	15.9	16.0	97.8	32.3	14.8	14.9	90.9
1986	16.2	16.0	104.5	30.8	14.8	14.6	95.3
1987	16.9	16.0	110.0	29.9	14.9	14.1	96.8
1988	18.2	16.0	122.2	28.1	15.4	13.5	103.3
1989	21.8	16.0	127.5	26.5	17.6	12.9	102.8

Source: Tobacco Institute (1994), USDHHS (1994).

¹ These percentages cannot be calculated directly from the tax and price information because taxes are weighted average taxes for the entire fiscal year while prices and percentages are generally as of November 1.

² Real taxes and prices are obtained from nominal amounts using the urban consumer price index (CPI-U, 1982-1984=100). All data are for the fiscal year ending June 30.

³ States taxes are a weighted average of the tax in taxing states and the District of Columbia. Price refers to the average retail price in all states and the District of Columbia.

Table 3.2: Cigarette Taxes and Cigarette Prices per Pack, 1975 – 1989

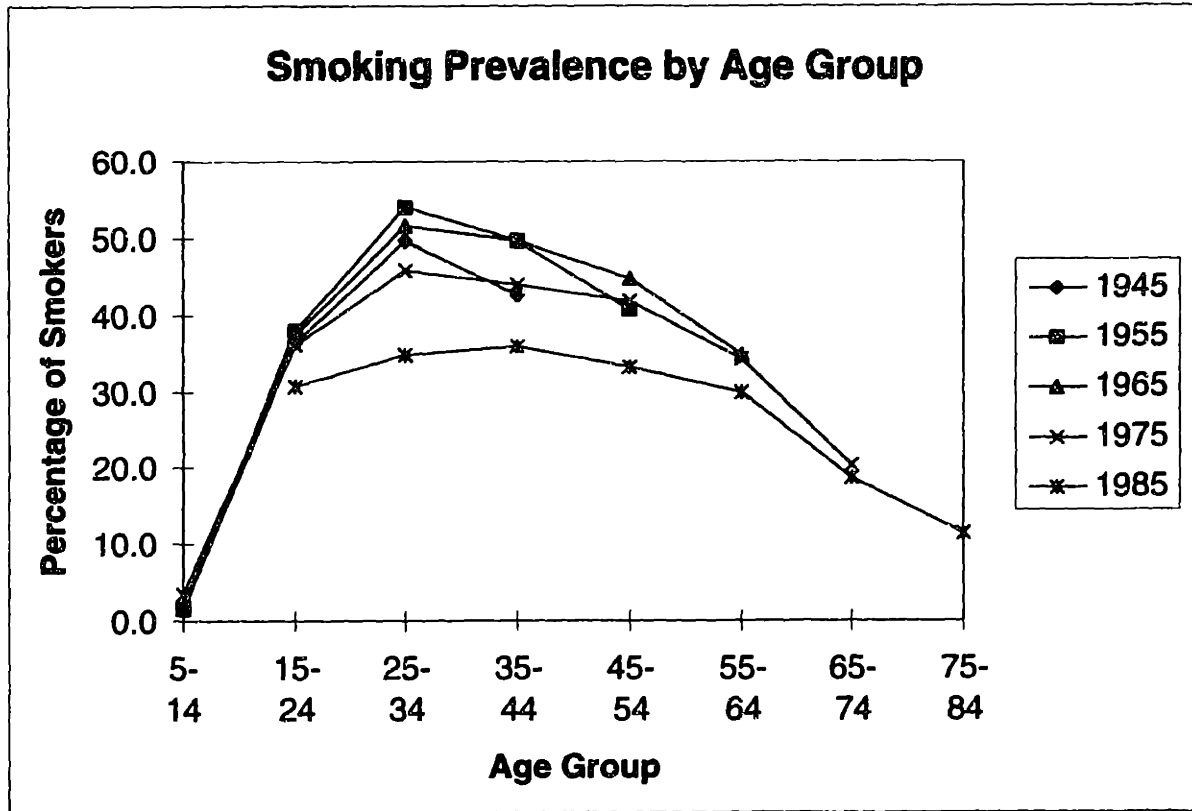


Figure 3-2: Smoking Prevalence by Age Group Derived from Prevalence of Cigarette Smoking Over Time Among Successive Birth Cohorts Based on National Health Interview Surveys (1970, 1978, 1979, 1980 and 1987).

is much less severe in subsequent years. In particular, the national smoking prevalence data in Figure 3-2, which was derived from National Health Interview Survey (NHIS) findings, suggest that measurement error may not be a serious problem for the 1975 to 1989 state panel data.³

The next two sections describe the specifications, data, and estimates for the state

³Using data from the NHIS conducted in 1970, 1978, 1979, 1980, and 1987, the prevalence of cigarette smoking over time among successive birth cohorts can be derived (which is equivalent to finding the percentage of smokers by certain age groups) for the years from 1950 to 1987 (USDHHS 1991). Because of its large sample size and high response rate (typically greater than 95%), the NHIS provides highly reliable estimates of national smoking prevalence in the United States. Of all the NHIS samples, the 1970 NHIS is the largest with 116,446 cases overall, including smoking data for 76,675 of these cases. For the other surveys used in this analysis, the total number of cases were 12,111 (1978), 26,271 (1979), 11,333 (1980), and 22,043 (1987).

panel data and national time series that will be used to test for market power and dynamic pricing effects.

3.3.1 State Cigarette Prices, 1971 - 1989

Specification

Consider a linear regression specification that for each state i relates the price of cigarettes at time t to the percentage of non-smoking children in the population, the ratio of young to adults, the ratio of middle-aged to seniors, and other variables that affect the price of cigarettes. The regression equation then takes the form

$$\begin{aligned}
 p_{it} = & \alpha_0 + \alpha_1 (\%Children)_{it} + \alpha_2 (Young/Old)_{it} & (3.9) \\
 & + \alpha_3 (Senior/Middle-aged)_{it} + \alpha_4 (Income)_{it} \\
 & + \alpha_5 (Marketing)_{it} + \alpha_6 (Manufacturing Wage)_{it} \\
 & + \alpha_7 (PPI)_{it} + \epsilon_{it},
 \end{aligned}$$

where

p_{it} = the average retail, or net-of-tax retail, price for cigarettes in state i in year t ,

$\%Children$ = the percentage of children 13 years old or younger relative to the total population less than or equal 65 years old,⁴

$Young/Old$ = the ratio of the population between 14 and 24 years old to the population between 24 and 65 years old expressed as a percentage,

$Senior/Middle-aged$ = the ratio of the population between 45 and 64 years old to the population between 24 and 44 years old expressed as a percentage,

$Income$ = the average personal income in state i in year t ,

⁴The percentage of children in the population is expressed as a percentage of the total population 65 years old and younger because the number of smokers in the population begins to fall rapidly after age 65 as the health effects of smoking take their toll.

Marketing = the total national cigarette advertising and promotional expenditures by all manufacturers in year t ,

ManufacturingWage = the national average annual wage for all manufacturing workers in year t , and

PPI = the producer price index for tobacco leaf in year t .

Since price and marketing are potentially endogenous variables, one would like to instrument for marketing in this regression rather than to assume, as here, that marketing is exogenous. The search for an appropriate instrument is complicated, however, by the dramatic shift in the composition of cigarette marketing from predominately advertising early in the sample to mainly direct mail by the end of the sample, as described in the Appendix.

State-specific factors, such as its religious composition, level of education, and military presence, may affect the demand for cigarettes in a state. Time-specific factors, such as economy wide shocks or changes in the smoking laws or the tar and nicotine content of cigarettes, also may influence demand. To incorporate the potential influence of such effects, the specification is estimated with state and time fixed effects, both separately and jointly. Thus the error term is decomposed as $\epsilon_{it} = \nu_i + \tau_t + \omega_{it}$, where ν_i is the state fixed effect and τ_t is the year fixed effect. When both state and time fixed effects are included, the coefficients are identified from within-state (over time) variation in demographic composition that cannot be explained by economy-wide shocks to demographics or price levels. While state and year fixed effects have the advantage that they may control for potentially important omitted variables, they have the twin disadvantages of reducing the remaining variation used to estimate the parameters and increasing the number of parameters to be estimated. As a result, the parameter estimates of the fixed effects models may be less precise.

With this specification, one can construct specific tests for market power and dynamic pricing effects in the cigarette industry. Under the null hypothesis of perfect competition, the coefficients, α_1 , α_2 , and α_3 , on the demographic variables should all be zero since

under the null the price is a function only of marginal cost. But if cigarette firms do have market power, the coefficient, α_2 , on the ratio of young to old should be negative, since the young have a significantly more elastic demand for cigarettes than the old.

One can also test for dynamic pricing effects, assuming that they are not confounded by different elasticities among groups of the population. If cigarette companies maximize profits only for the current period, the coefficient, α_1 , on the percentage of children in the population should be zero. But if cigarette manufacturers optimize dynamically, taking into account that today's children are tomorrow's potential young smokers, the coefficient α_1 should be positive. Similarly, dynamically optimizing firms should respond to the relative numbers of middle-aged and seniors in the population, which does not matter to the single period optimizer. In this case, one expects the coefficient, α_3 , on the ratio of seniors to middle-aged to be significant. If middle-aged and seniors have the same price elasticity of demand for cigarettes, α_3 should also be positive, but the sign of the coefficient depends on the relative elasticity between the two groups, which has not been measured.

Data

The state panel data set used to estimate this specification includes variables for the fifty states and the District of Columbia from 1975 to 1989. Table 3.3 presents the summary statistics for the state panel data set. Columns 1 and 2 report the mean and standard deviation for each independent variable while the last two columns give its range. Although summary statistics from single-year cross-section data sets are not reported in Table 3.3, the coefficient of variation for the retail price in each of the cross-section years ranges from eight to eleven percent while that for the net-of-tax price varies from six to eight percent. States also exhibit substantial variation in the demographic variables. For each of the age cohorts, the coefficient of variation is roughly ten percent. There are larger variations between the maximum and minimum and in the demographic structures of states over time. The youngest states have about one-quarter to one-third

of their population in the youngest two age cohorts (0 to 13 and 14 to 24 years) while older states have roughly half that. The sources of the state panel data are given in the Appendix. All nominal values have been converted to real amounts using the urban consumer price index, CPI-U, where 1982-1984 = 100.

Results

The results of estimating equation 3.9 using state retail and net-of-tax retail prices are presented in Tables 3.4 and 3.5, respectively. The retail price regressions analyze the relationship between demographic variables and price while controlling for other factors, and the net-of-tax retail price regressions serve as a proxy for unobserved state wholesale prices. The analysis covers all fifty states plus the District of Columbia from 1975 to 1989 for a total of 765 state-year observations. Estimates from the pooled regression, which includes neither state nor time fixed effects, are given in the first column of the tables. The second through fourth columns contain the results from estimating equation 3.9 with (a) state fixed effects, $\epsilon_{it} = \nu_i + \omega_{it}$, labeled ST FE, (b) year dummy variables, $\epsilon_{it} = \tau_t + \omega_{it}$, marked YR FE, and (c) both state and year fixed effects, $\epsilon_{it} = \nu_i + \tau_t + \omega_{it}$, denoted SY&YR FE. In this and all subsequent regression tables, the estimated coefficients correspond to the variables listed to their left with their standard errors listed below them in parentheses. All regression models are corrected for heteroskedasticity and within state, first-order autocorrelation in their errors.

Consider first the retail price regression entitled Pooled. The coefficient on the ratio of young to old is negative and significant and considerably larger than that predicted by the Bertrand model. The estimate indicates that for an increase in the ratio of young to old of one standard deviation (14%), the regression model predicts a price decline of \$0.11 or 13% of the mean retail price. The coefficients on both the percentage of children and the ratio of senior to middle-aged are positive and significant. Increasing the percentage of younger children by one standard deviation (2.4%) leads to a price increase of \$0.061 or 7% of the mean retail price. An increase of one standard deviation (15%) in the ratio of

Variable	Std.			
	Mean	Dev.	Min.	Max.
Price (¢)	85.6	13.0	54.3	123.0
Tax (¢)	29.0	7.5	10.0	53.9
Net-of-tax Price (¢)	56.5	10.7	40.5	91.7
Percent 0-13 years*	24.2%	2.4%	17.0%	33.6%
Young/Old $\left(\frac{n_{14-24} * 100}{n_{25-64}}\right)$	40.9	5.81	27.7	59.5
Senior/Middle-aged $\left(\frac{n_{45-64} * 100}{n_{25-44}}\right)$	66.0	10.2	35.6	97.7
Personal Income (\$)	12,108	2,106	7,697	20,385
PPI for Tobacco Leaf	84.4	14.4	59.4	101.5
Manufacturing Wage (\$/week)	359	10.8	343	382
National Marketing (\$ millions)	1,839	563	913	2,917

* Percentages are defined relative to the total population under 65 years. Monetary values are reported in 1982 dollars with deflation across years using the CPI-U (1982-1984=100). The sample consists of fifty states plus the District of Columbia for the years 1975-1989.

Table 3.3: Summary Statistics: State Panel Data, 1975 – 1989

Retail Price	Pooled	ST FE	YR FE	ST&YR FE
Percent 0 - 13 years*	2.522 (0.269)	2.607 (0.398)	1.001 (0.165)	1.214 (0.268)
Young/Old	-1.894 (0.117)	-2.317 (0.162)	-0.391 (0.091)	-0.052 (0.135)
Senior/Middle-aged	0.370 (0.056)	0.381 (0.107)	0.339 (0.048)	0.171 (0.067)
Personal Income	1.558 (0.252)	2.394 (0.412)	1.402 (0.190)	-0.149 (0.237)
Marketing	0.748 (0.099)	0.480 (0.116)	1.611 (0.091)	1.952 (0.148)
PPI for Tobacco Leaf	-0.225 (0.032)	-0.224 (0.033)	-0.295 (0.026)	-0.344 (0.024)
Manufacturing Wage	22.850 (1.941)	22.607 (1.879)	—	—
Constant	-17.582 (14.567)	-0.581 (17.230)	35.509 (12.231)	42.175 (17.581)
State Dummies	—	Yes	—	Yes
Year Dummies	—	—	Yes	Yes
N	765	765	765	765
Log Likelihood	-1747	-1675	-1387	-1292

* Percentages are defined relative to the total population under 65 years.

Table 3.4: State Retail Cigarette Price Regressions, 1975 - 1989

senior to middle-aged results in a retail price increase of \$0.038, or 4% of the mean. Each of the control variables – personal income, marketing, producer price index for tobacco leaf, and manufacturing wage – is positive and significant in the regression exception for the cost of tobacco leaf, which is negative and significant. During the sample period, manufacturers made increasingly efficient use of tobacco and reduced the tobacco leaf content of cigarettes, which may account for this negative coefficient.

The addition of state or year fixed effects, or both, to the regression generally reduces the magnitudes of the coefficients of interest moving from left to right across the table. The coefficient on the ratio of young to old is negative in all specifications and significant in all but the last which includes both state and year fixed effects. Its magnitude ranges from -2.317 in state fixed effects model to -0.052 when both state and year fixed effects are added. The coefficients for the percentage of children and the ratio of senior to middle-aged are positive and significant in all specifications, although adding year fixed effects appears roughly to halve their magnitudes. The coefficient on personal income decreases and then becomes insignificant with the addition of fixed effects, while the coefficients for marketing and tobacco leaf remain significant and increase in size. As in the pooled regression, the coefficient for tobacco leaf is of the opposite sign expected. Note that the manufacturing wage has been omitted from regressions that include year fixed effects as it was colinear with other variables in the regression.

The results of the same analysis using the net-of-tax retail price as the dependent variable instead of the retail price are given in Table 3.5. Overall the results are similar to, but smaller and less precisely estimated than, those for the retail price for the percentage children, the ratio of young to old, and the control variables. The main difference appears in the coefficient for the ratio of senior to middle-aged which is negative and of opposite sign to that for the retail price. As in the retail price regressions, controlling for state and year fixed effects reduces the precision of the estimates, but in the case of the net-of-tax regressions to the point that several estimates of interest, although of the same sign, are no longer significant.

Net-of-Tax Price	Pooled	ST FE	YR FE	ST&YR FE
Percent 0 - 13 years*	0.828 (0.124)	1.095 (0.235)	0.393 (0.124)	0.417 (0.186)
Young/Old	-0.844 (0.069)	-1.150 (0.092)	-0.196 (0.077)	0.049 (0.091)
Senior/Middle-aged	-0.133 (0.028)	-0.055 (0.060)	-0.120 (0.033)	0.041 (0.046)
Personal Income	0.715 (0.114)	1.493 (0.260)	0.754 (0.129)	0.130 (0.165)
Marketing	1.129 (0.068)	0.882 (0.087)	1.141 (0.076)	1.534 (0.099)
PPI for Tobacco Leaf	-0.160 (0.019)	-0.123 (0.022)	-0.002 (0.020)	0.022 (0.018)
Manufacturing Wage	11.704 (1.540)	11.853 (1.338)	--	--
Constant	22.167 (8.845)	20.023 (11.901)	35.041 (8.633)	12.313 (12.287)
State Dummies	—	Yes	—	Yes
Year Dummies	—	—	Yes	Yes
N	765	765	765	765
Log Likelihood	-1611	-1518	-1183	-1063

* Percentages are defined relative to the total population under 65 years.

Table 3.5: State Net-of-Tax Cigarette Price Regressions, 1975 – 1989

Cross Border Regressions

Since firms must price discriminate among states to exercise their market power and dynamically optimize, one would expect to see greater price discrimination where it is easier to discriminate. This provides another potential test of the market power and dynamic pricing hypotheses. In the final chapter of this thesis, cross border effects, resulting from citizens crossing state boundaries to buy cheaper cigarettes, are found to be important in New Hampshire, Rhode Island, and Vermont. Other empirical studies suggest that, due to their small size and proximity to large cities in neighboring states, Delaware and the District of Columbia may also experience cross border shopping. As a result, these states will have difficulty maintaining higher prices than those prevalent in adjacent states, making price discrimination more difficult in states with cross border effects. This suggests testing whether more price discrimination exists among states without cross border effects.

By adding a dummy variable for cross border states and interaction terms for the demographic variables of interest to the specification of equation 3.9, the regression equation becomes

$$\begin{aligned}
 p_{it} = & \alpha_0 + \alpha_1 (\%Children)_{it} + \alpha_2 (\delta_{XB} * \%Children)_{it} & (3.10) \\
 & + \alpha_3 (Young/Old)_{it} + \alpha_4 (\delta_{XB} * Young/Old)_{it} \\
 & + \alpha_5 (Senior/Middle-aged)_{it} + \alpha_6 (\delta_{XB} * Senior/Middle-aged)_{it} \\
 & + \alpha_7 (Income)_{it} + \alpha_8 (Marketing)_{it} + \alpha_9 (ManufacturingWage)_{it} \\
 & + \alpha_{10} (PPI)_{it} + \alpha_{11} \delta_{XB} + \epsilon_{it},
 \end{aligned}$$

where δ_{XB} equals one if state i may experience cross border effects and δ_{XB} is zero otherwise. Two different sets of cross border states are considered. The first consists of five states, Delaware, District of Columbia, New Hampshire, Rhode Island and Vermont, and the second includes ten states, the five states in the first set plus Connecticut, Missouri, New Jersey, New York and Pennsylvania.

The results of this regression for the retail cigarette price are presented in Table 3.6. If price discrimination is more difficult in cross border states, one would expect the influence of the demographic variables, *%Children*, *Young/Old*, and *Senior/Middle-aged*, to be diminished. The results of the pooled regression in Table 3.6 bear this out. The coefficients on the interaction terms, for example α_2 , have the opposite sign of those on the corresponding variables, α_1 in the example, and are significant in all but one case. For the five state regression, the size of the effect ranges from a coefficient reduction of 12% for *Young/Old* to a 69% drop in the *%Children* coefficient. A test of whether the coefficients of the interaction terms are jointly zero strongly rejects the null with a χ^2 statistic with three degrees of freedom of 40.23 in the five state regressions and a χ^2 statistic with three degrees of freedom of 24.94 for ten cross border states.

3.3.2 National Wholesale Cigarette Prices, 1950 - 1993

Specification

The national time series data provide a quick look at the effect of national demographics on wholesale cigarette prices. The longer period of the time series has the advantage of the greater demographic changes over more than forty years, but this apparent advantage is offset by the substantial changes in cigarette demand, regulation, and health information, which may confound the results. The specification for the time series regressions is similar to that for the state panel regressions, equation 3.9, with the state index, i , suppressed and slightly different demographic variables. The national wholesale list price is a function of the demographic and control variables

$$\begin{aligned}
 p_t = & \alpha_0 + \alpha_1 (\%Children)_t + \alpha_2 (Young/Old)_t & (3.11) \\
 & + \alpha_3 (Senior/Middle-aged)_t + \alpha_4 (Income)_t \\
 & + \alpha_5 (Marketing)_t + \alpha_6 (ManufacturingWage)_t \\
 & + \alpha_7 (PPI)_t + \epsilon_t,
 \end{aligned}$$

Retail Price	5 States	10 States
Percent 0 - 13 years*	3.215 (0.289)	2.235 (0.214)
δ_{XB} * Percent 0 - 13 years*	-2.207 (0.465)	-1.822 (0.406)
Young/Old	-2.017 (0.117)	-1.137 (0.111)
δ_{XB} * Young/Old	0.251 (0.297)	0.559 (0.202)
Senior/Middle-aged	0.426 (0.056)	0.474 (0.057)
δ_{XB} * Senior/Middle-aged	-0.187 (0.155)	-0.131 (0.088)
Personal Income	1.546 (0.244)	2.049 (0.227)
Marketing	0.737 (0.096)	1.759 (0.116)
PPI for Tobacco Leaf	-0.207 (0.031)	-0.295 (0.034)
Manufacturing Wage	24.073 (1.908)	22.894 (3.072)
δ_{XB}	56.371 (9.446)	28.357 (8.241)
Constant	-39.317 (14.562)	-68.002 (17.282)
N	765	765
Log Likelihood	-1734	-2251

* Percentages are defined relative to the total population under 65 years.

Table 3.6: Cross Border Regressions, 1975 – 1989

where the only variables redefined are:

p_t = the national wholesale list price for cigarettes in year t ,

$\%Children$ = the percentage of children 15 years old or younger relative to the total population less than or equal 65 years old,⁵

$Young/Old$ = the ratio of the population between 16 and 24 years old to the population between 24 and 65 years old expressed as a percentage,

$Senior/Middle-aged$ = the ratio of the population between 45 and 64 years old to the population between 24 and 44 years old expressed as a percentage, and

$Income$ = the average disposable personal income in state i in year t .

For the national series, children are defined as those 15 years old or under (as opposed to 13 years old or under for the state panel) while the young are those between 16 and 24 years of age (versus 14 to 24 years for the state panel). The definitions of middle-aged and senior are the same as those for the state panel, 25 to 44 years old and 45 to 64 years old, respectively.

The coefficients used to test for market power and dynamic pricing effects are the same as those for the state panel regressions: the coefficients on the percentage of children, α_1 , on the ratio of young to old, α_2 , and on the ratio of senior to middle-aged, α_3 . As in the state panel regressions, income, marketing, manufacturing wage and cost of tobacco leaf are included as regressors to control for other factors affecting demand or costs.

Data

The national time series data, 1950 to 1993, cover twenty five years more than the state panel data, 1975 to 1989. Table 3.7 presents the summary statistics for the national time series data, and the Appendix contains further information about the data and its sources. All nominal values have been converted to real amounts using the urban consumer price index, CPI-U [1982-1984 = 100]. The wholesale price is the national

⁵The percentage of children in the population is expressed as a percentage of the total population 65 years old and younger because the number of smokers in the population begins to fall rapidly after age 65 as the health effects of smoking take their toll.

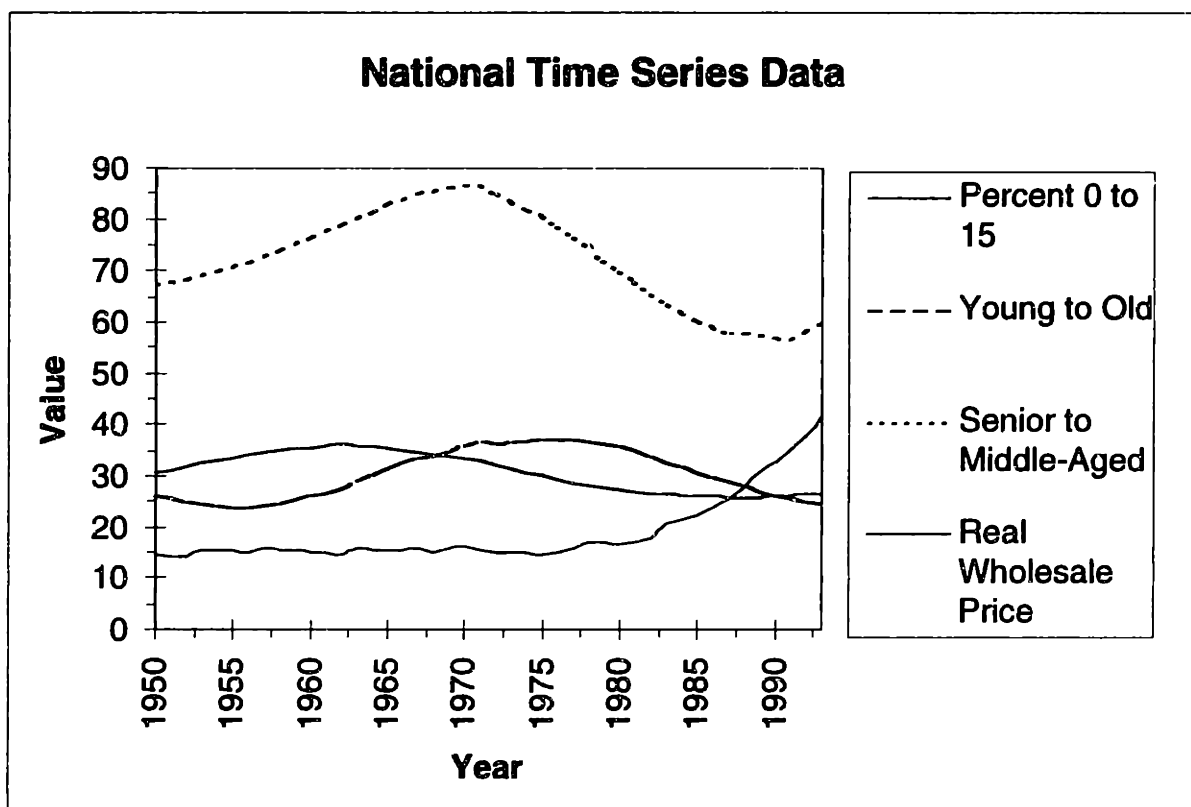


Figure 3-3: National Time Series Data Including Percentage of U.S. Population Aged 0–15 Years and Ratios of Young (16–24 years) to Old (24–65) and Senior (45–65) to Middle-Aged (24–44) Expressed as Percentages.

listed wholesale price for 1,000 cigarettes, which is equivalent to 50 packs of 20 cigarettes each. Data on selected variables for the national time series are presented in Figure 3-3, which shows that most of the variation in the wholesale price occurred after 1975, suggesting that the state panel data may provide better test of the proposed hypotheses.

Results

Table 3.8 presents the regression results for the national time series. The first two columns contain the least squares results for the entire 44 years of the sample. Since marketing expenditures are available only since 1975, the last two columns report the estimates for only on 19 yearly observations. All estimates are corrected for first-order serial correlation

Variable	Mean	Std.	Min.	Max.
		Dev.		
Wholesale Price (\$)	18.90	6.98	14.00	41.59
Percent 0-15 years*	31.1%	3.8%	26.0%	36.5%
Young/Old $\left(\frac{n_{16-24} * 100}{n_{25-64}}\right)$	30.5	4.8	24.0	37.2
Senior/Middle-aged $\left(\frac{n_{45-64} * 100}{n_{25-44}}\right)$	72.5	9.7	56.7	86.8
Disposable Personal Income (\$)	9,153	2,265	5,673	12,570
PPI for Tobacco Leaf	57.9	28.3	26.9	101.5
Manufacturing Wage (\$/week)	331	38	240	382
National Marketing (\$ millions)**	2,209	917	913	4,176

* Percentages are defined relative to the total population under 65 years. Monetary values are reported in 1982 dollars with deflation across years using the CPI-U (1982-1984=100).

** Available only for 1975 to 1993.

Table 3.7: Summary Statistics: National Time Series Data, 1950 – 1993

using the Prais-Winsten method. The correlation coefficient, ρ , and the Durbin-Watson statistics, DW, for the original and the transformed data are reported together with the adjusted R^2 statistic in the bottom rows of the table. The Durbin-Watson statistics reveal significant serial correlation in the errors of those regressions employing the entire time series that do not account for autocorrelation.

The coefficient on the ratio of young to old is negative and statistically significant in all the national time series regressions. From the parameter estimates from column II, an increase of one standard deviation (15.7%) in the mean ratio of young to old would result in a wholesale price decrease of \$7.09, roughly 37.5% of the mean wholesale price. The coefficient on the percentage of the population under 15 years of age alternates signs and is not, with one exception (column III) where it is positive, significant in any of the regressions. The coefficient on the ratio of senior to middle-aged is positive in all cases and significant in all but column IV where it is nearly significant at the 10% level ($p = 0.110$). Based on the result from column V, increasing the ratio of senior to middle-aged by one standard deviation (13.3%) would increase the wholesale price of cigarettes by \$5.98 or 31.6% of its sample mean. These effects seem quite large and suggest that other, omitted factors, such as the increasing regulation of cigarette advertising or growing health concerns about smoking, may affect the results.

The control variables have the expected signs with the exception of the manufacturing wage. Since during this time period plant efficiencies increased as more automated machinery replaced labor while at the same time manufacturing wages increased, the negative coefficient on wages may reflect this inverse correlation. Although not all control variables are individually significant,⁶ each is strongly significant in the regression that includes all controls in the complete sample (column II), and they are jointly significant in the shortened sample that includes marketing expenditures (column IV).

⁶This is shown in separate regressions not reported here.

Wholesale Price	I	II	III	IV
Percent 0 - 15 years*	-0.340 (0.437)	0.063 (0.258)	1.449 (0.381)	-0.436 (0.928)
Young/Old	-1.102 (0.286)	-1.478 (0.233)	-2.761 (0.464)	-1.215 (0.400)
Senior/Middle-aged	0.487 (0.226)	0.616 (0.178)	0.800 (0.251)	0.626 (0.360)
Disposable Income		4.598 (0.516)		2.921 (1.488)
PPI for Tobacco Leaf		0.118 (0.037)		0.047 (0.055)
Manufacturing Wage		-6.248 (2.307)		-2.811 (3.381)
Marketing			0.024 (0.135)	0.380 (0.195)
Constant	120.87 (21.51)	-11.337 (3.564)	21.832 (5.189)	-2.238 (7.080)
ρ	0.994 (0.002)	0.716 (0.067)	0.718 (0.030)	-0.150 (0.237)
DW (original)	0.068	0.829	1.658	2.126
DW (transformed)	1.560	1.930	2.370	2.107
N	44	44	19	19
Adj. R ²	0.264	0.898	0.957	0.995

* Percentages are defined relative to the total population under 65 years.

Table 3.8: National Wholesale Cigarette Price Regressions: 1950 – 1993

3.3.3 Discussion of Empirical Results

Two data sets were used to test for market power and dynamic pricing in the cigarette industry: a state panel 1975 to 1989 and a national time series from 1950 to 1993. The state panel has several advantages over the time series. First, the state panel covers a shorter period during which concerns about smoking and health and anti-smoking legislation remained largely stable. Second, the panel permits the use of its cross-sectional variation in testing various hypotheses. The time series suffers from fewer observations over nearly a forty-five year period during which many factors affecting smoking behavior, not the least of which are health concerns, changed substantially.

To assess the evidence for market power in the cigarette industry, consider first the effect of the demographic age variables on price. All the specifications for both the state panel and national time series reject the joint hypothesis that the percentage of young children, the ratio of young to old, and the ratio of senior to middle-aged all have zero coefficients as would be the case in a perfectly competitive market. From the results of changing the state panel specifications, however, it is clear that fixed effects do change the estimates.

The most robust results are those for the ratio of young to old, which is negative in all state and national specifications and significant for all but the state panel regression with both state and year fixed effects. This lack of significance may have been induced by the addition of both fixed effects as evidenced by the smaller estimates and larger standard errors obtained. Although the state and year fixed effects correct for possible deficiencies in that data, which do not properly account for variations in unobserved factors among states and over time, they extract a price in terms of reducing the amount of variation available for estimation.

In the results for the state panel and time series, the elasticity of price with respect to the ratio of young to old is higher for the time series than the state panel. This suggests that, given the substantial changes in patterns of demand from 1950 to 1993, it is important to correct for year effects. The size of the coefficient predicted by the

Bertrand model, of order 0.3, also suggests that the larger estimates from the pooled and state fixed effects models may be too large and that the estimate with year fixed effects might be preferable.

Taken together these results suggest that cigarette firms exercise market power subject to two additional caveats. One is that other types of specification errors could bias the results, the lack of instruments for marketing, for example. The second is the absence of a cost of capital or capital stock variable for cigarette manufacturers and the lack of an adequate proxy for regulations and health concerns.

The evaluation of evidence for dynamic pricing is more challenging. One must consider whether the observed pricing effects can be explained in terms of different elasticities in different segments of the population. The elasticities of young and old smokers have been measured, but this is not true for other age groups. If, for example, senior smokers have a more inelastic demand for cigarettes than their middle-aged counterparts, one would observe that prices rise when the proportion of senior to middle-aged is higher, but this would be the result of their different elasticities rather than the result of dynamic pricing by the firms in the industry. Similarly, if middle-aged parents with children have lower elasticities than adults without children, one might observe that prices rise when the number of children increases, but this would be due to an increase in the number of middle-aged parents rather than to forward-looking firm behavior.

To resolve whether the observed effects might be explained by differences in elasticities rather than dynamic effects, a few back-of-the-envelope calculations are quite informative. The details of the following computations may be found in the Appendix. Assume that cigarette companies exercise market power and that markups follow the standard conjectural variations model,

$$\frac{p - c}{p} = \frac{\theta}{\varepsilon},$$

where θ is a measure of market power and equal to $1/n$ for a Cournot model with n firms. From the observed aggregate elasticity, ε , the observed price, p , and marginal cost, c , one can derive a value for θ . Since the aggregate elasticity is the population share weighted

average of elasticities among groups in the population, one can then calculate the effect of changing shares or elasticities on the price by taking appropriate derivatives of the above equation.

For reasonable estimates of these parameters, one finds that only a small difference, of order 0.04, in the price elasticities of demand for middle-aged and senior smokers suffices to explain the size of the estimated coefficient on the ratio of senior to old. Since the elasticities of demand for cigarettes are not known to this precision, such a test will not be able to discriminate between dynamic effects and differences in elasticities.

Similarly, one can ask what elasticity difference between adult smokers with and without children would be required to explain the observed coefficient on the percentage of children in the population. Here the answer is more reassuring as an unreasonably large difference in the elasticities would be required. Thus different elasticities do not seem plausible as an explanation for the size of the observed effect on the percentage of children.

The case for dynamic pricing therefore rests on the strength of the evidence for the proportion of children in the population having an effect on cigarette prices. In the state panel regressions, the coefficient for percent children is positive and significant in all specifications, including that with both state and fixed effects. The inclusion of year fixed effects, however, reduces the size of the estimate by about half that estimated without such fixed effects suggesting that controlling for changes over time is important. Changes in the fraction of children also have significant economic effects. Using the smallest estimate of the state panel results (from the state fixed effects regression in Table 3.4), an increase one standard deviation (2.4%) in the percentage of children leads to a price increase of \$0.024 or 2.8% of the mean retail price.

Conversely, the estimates from the time series regression are insignificant in both fully controlled specifications (columns II and IV in Table 3.8). The insignificance of the national time series estimates may in part result from the different definitions of the age group for children used in the state panel (0 to 13 years) and time series (0 to 15 years)

regressions since significant numbers of children experiment with smoking between the ages of 13 and 15. Or, as previously mentioned, either or both regressions may suffer from misspecification.

3.4 Conclusion

This study reaches several conclusions about market power and dynamic pricing in the cigarette industry. The state panel and national time series results concur that the age distribution of consumers is correlated with cigarette prices. This suggests that market for cigarettes was not perfectly competitive during the time period studied. Evidence for dynamic pricing effects is less conclusive. The test for a significant coefficient on the ratio of senior to middle-aged is easily confounded by small differences in the elasticities for the two age groups. Thus, only the percentage of children in the population serves as a practical test for dynamic effects. But the percentage of children is positive and significant only in the state panel regressions and not in the national time series, although its insignificance in the time series may be due to the inclusion of 13 and 14 year olds as children in the time series regressions. Consequently, the evidence for dynamic pricing effects must be considered tentative. These results, however, are consistent with the earlier, unpublished work of Showalter (1995), who also finds evidence for forward-looking firm behavior using a different methodology, and, like those of Showalter, these results are not consistent with the rational addiction models of Becker and Murphy (1988).

3.5 Appendices

3.5.1 Effect of Elasticity Differences on Coefficient Estimates

This section of the Appendix sets forth back-of-the-envelope calculations of the elasticity differences between subgroups of the population required to explain the observed coefficient estimate for the percentage children and the estimate for senior to middle-aged.

Assume that cigarette companies exercise market power and that markups follow the standard conjectural variations model,

$$\frac{p - c}{p} = \frac{\theta}{\varepsilon}, \quad (3.12)$$

where θ is a measure of market power and equal to $1/n$ for a Cournot model with n firms. From the observed aggregate elasticity, $\varepsilon = -0.5$, the state panel sample mean price, $p = 85.6$, and an estimate of marginal cost, $c = 40$, one can obtain a value for $\theta = 3.75$, which corresponds most closely to a 4-firm Cournot model.

Solving equation 3.12 for price as a function of cost yields

$$p = \left[\frac{1}{1 - \frac{\theta}{\varepsilon}} \right] c. \quad (3.13)$$

The aggregate elasticity, ε , is the population share weighted average of elasticities among groups in the population. For three groups with population shares, s_1 , s_2 , and s_3 , the elasticity is

$$\varepsilon = s_1\varepsilon_1 + s_2\varepsilon_2 + s_3\varepsilon_3. \quad (3.14)$$

Substituting for the elasticity in equation 3.13 gives price as a function of the shares and elasticities of groups comprising the population. By taking appropriate derivatives and substituting the observed values for the parameters, one obtains an estimate of how the price changes as a function of changes in the underlying demographics. For example, the derivative of price with respect to share i is

$$\frac{\partial p}{\partial s_i} = \frac{-c\theta}{(\varepsilon - \theta)^2} \frac{\partial \varepsilon}{\partial s_i}. \quad (3.15)$$

Coefficient on the Percentage Children

Consider whether a difference in the elasticities of adults with and without children could explain the observed coefficient on the percentage of children. Since the coefficient is positive, parents with children must have more inelastic demands than those without for this explanation to work.

Assume three cohorts, nonsmoking children, young and adult, with shares s_0 , s_1 , and s_2 . Suppose only adults have children. The share of adult smokers, s_2 , can be further divided into the share, s_2^k , of middle-aged, who do have younger, nonsmoking children, and the share, s_2^{nk} , of the seniors who do not, so that $s_2 = s_2^k + s_2^{nk}$. The aggregate elasticity is then $\varepsilon = s_1\varepsilon_1 + s_2\varepsilon_2 = (1 - s_2)\varepsilon_1 + s_2\varepsilon_2$, since children do not smoke.

How large an elasticity difference would there have to be between these the middle-aged and seniors to explain the observed coefficient of the price response to the percentage, s_0 , of children in the population $\frac{\partial p}{\partial s_0}$? If we assume that the number of younger children equals the number of middle-aged parents who have children, the $s_0 = s_2^k$ and therefore

$$\begin{aligned} \frac{\partial p}{\partial s_0} &= \frac{\partial p}{\partial s_2^k} = \frac{\partial p}{\partial s_2} \frac{\partial s_2}{\partial s_2^k} = \frac{\partial p}{\partial s_2} \\ &= \frac{-c\theta}{(\varepsilon - \theta)^2} (s_2^k \varepsilon_2^k + s_2^{nk} \varepsilon_2^{nk} - \varepsilon_1). \end{aligned}$$

where ε_2^k and ε_2^{nk} are the elasticities of the adult age groups with and without children respectively. Let $\varepsilon_2^k = \varepsilon_2^{nk} - \delta$. We want to find δ , the elasticity difference required explain the observed coefficient. Using the observed values of the parameters of $\theta = 0.25$, $c = 40$, $\varepsilon = -0.5$, $\varepsilon_2^{nk} = -0.42$, the population shares from the means of the state panel data, $s_2^k = 0.327$ and $s_2^{nk} = 0.213$, and with the estimated coefficient of 1.2, one finds that $\delta = -4.8$. Such a difference in elasticities is implausibly large so the possibility that different elasticities within different types of households can explain the observed effect

seems unlikely.

Coefficient on Ratio of Senior to Middle-Aged

Consider now whether the estimate on the ratio of senior to middle-aged can be explained by a difference between the two groups in their price elasticities of demand for cigarettes. Assume there are three cohorts, young, middle-aged, and senior, whose shares of the smoking population are respectively, s_1 , s_2 , and s_3 . We are interested in $\frac{\partial p}{\partial \left(\frac{s_3}{s_2}\right)}$. Assume that the share of the young, s_1 , is constant. Since the shares must sum to one, the formula for the elasticity of demand, equation 3.14, can be expressed as a function of $\frac{s_3}{s_2}$ and s_1 and

$$\frac{\partial p}{\partial \left(\frac{s_3}{s_2}\right)} = \frac{c\theta}{(\varepsilon - \theta)^2} \left(\frac{1 - s_1}{\left(1 + \frac{s_3}{s_2}\right)^2} \right) (\varepsilon_2 - \varepsilon_3).$$

The observed shares from the means of the state panel are $s_1 = 0.219$, $s_2 = 0.327$, and $s_3 = 0.213$, and the estimated coefficient is 0.3. Substituting these values in the above equation implies that the observed coefficient could be explained by an elasticity difference of 0.06. Since this small difference is well below the precision with which such elasticities can be estimated, one cannot rule out a difference in elasticities as the explanation for the observed effect.

3.5.2 Bertrand Model Predictions

To see how firm prices change in response to a small increase in the number of young smokers, differentiate p_i^{NE} with respect to n_1 :

$$\frac{dp_i^{NE}}{dn_1} = \frac{-n_2}{(2\beta - \gamma)^2} [(a_1c_2 - a_2c_1) + c(b_1c_2 - b_2c_1) + 2(a_2b_1 - a_1b_2)]. \quad (3.16)$$

Similarly, the firms adjust their equilibrium prices in response to small changes in the number of old smokers according to

$$\frac{dp_i^{NE}}{dn_2} = \frac{-n_1}{(2\beta - \gamma)^2} [(a_2c_1 - a_1c_2) + c(b_2c_1 - b_1c_2) + 2(a_1b_2 - a_2b_1)]. \quad (3.17)$$

Finally, the change in equilibrium prices resulting from a change in the ratio of young to old smokers, $r = n_1/n_2$, is given by

$$\frac{dp_i^{NE}}{dr} = \frac{2a_1b_2 - 2a_2b_1 + a_2c_1 - a_1c_2 + (b_2c_1 - b_1c_2)c}{((c_1 - 2b_1)r - 2b_2 + c_2)^2} \quad (3.18)$$

These derivatives can not be signed unambiguously without additional assumptions, but a brief calculation shows that for reasonable parameters corresponding to the empirically observed demands for cigarettes, $\frac{dp_i^{NE}}{dn_1}$ is always negative in this model and $\frac{dp_i^{NE}}{dn_2}$ is positive.

Consider the locus of points demarcating the boundary between positive and negative values of $\frac{dp_i^{NE}}{dn_1}$ in (c_1, c_2) -space. This is just a line given by setting the bracketed term in equation 3.16 to zero:

$$c_1 = \left(\frac{a_1 + b_1c}{a_2 + b_2c} \right) c_2 + \frac{2(a_2b_1 - a_1b_2)}{a_2 + b_2c}. \quad (3.19)$$

The key term is the intercept. As long as the value of the intercept exceeds b_1 , the bracketed term in equation 3.16 is always positive in the region $c_1 < b_1$ since the slope (coefficient on c_2) is positive.

Now substitute parameter values derived from the observed demand for cigarettes. Since the empirical analysis applies to aggregate demand and brand-specific price elasticities are not known, elasticities for the aggregate demand for cigarettes are used, although brand-specific elasticities would be expected to be more elastic. For example, suppose that the average young and the average old smoker each consumes one pack of cigarettes per day at a price $p = 100$ and that their respective elasticities of demand

are $\eta_1 = -1.4$ and $\eta_2 = -0.4$. The corresponding parameters for the model are then $a_1 = 2.4$, $a_2 = 1.4$, $b_1 = 0.014$, and $b_2 = 0.004$. Given the restriction that $b_k > c_k$ for each brand k , the line, defined by equation 3.19 lies to the right of the region of admissible c_k provided that $c < 167$, which exceeds p as well as any reasonable assumption for the marginal cost of a pack of cigarettes. Thus $\frac{dp_i^{NE}}{dn_1}$ is negative and $\frac{dp_i^{NE}}{dn_2}$ is positive.

3.5.3 Stochastic Dynamic Model

Consider now a population consisting of three cohorts, teenager, middle-aged and senior. To derive the effect of nonsmoking, younger children on the firm's pricing strategy simply redefine the cohorts as children, teenagers, and adult.⁷ The population of teenagers, N_{1t} , grows geometrically with time at a rate γ subject to some uncertainty described by the random variable $\bar{\epsilon}$, which has a probability distribution, $f(\bar{\epsilon})$, with mean zero and variance σ^2 .

$$N_{1t+1} = N_{1t}(\gamma + \bar{\epsilon}). \quad (3.20)$$

Of these teenagers, the fraction, $\varphi(p_t)$, who start smoking is a function of the current price of cigarettes, p_t . The number of teenage smokers in period t is then

$$n_{1t} = N_{1t}\varphi(p_t). \quad (3.21)$$

There are three age cohorts in the model: teenage, middle-aged, and older smokers. In the next period, teenager smokers become middle-aged smokers, middle-aged smokers become old smokers, and old smokers die. Recall that teenage smokers have a per capita demand of $d_1(p)$ that is more elastic than the demand of older, addicted smokers, $d_2(p)$.

⁷The derivation of this model is straight forward and has been omitted. Since the computation burden of the numerical calculations required to solve the dynamic stochastic problem increases geometrically with the number of state variables, a model with four age cohorts – children, teenagers, middle-aged and senior – has not been computed.

The total demand for cigarettes from these three age groups in period t is

$$q_t(p_t) = n_{1t}d_{1t}(p_t) + (n_{2t} + n_{3t})d_2(p_t), \quad (3.22)$$

where n_{1t} , n_{2t} and n_{3t} are, respectively, the number of teenage, middle-aged and older smokers.

Using equations 3.21 and 3.22, the firm's current profits are

$$\begin{aligned} \pi_t(N_{1t}, n_{2t}, n_{3t}, p_t) &= (p_t - c) q_t(p_t) \\ &= (p_t - c) (N_{1t}\varphi(p_t) d_{1t}(p_t) + (n_{2t} + n_{3t}) d_2(p_t)). \end{aligned} \quad (3.23)$$

The firm maximizes the present discounted value of its future profits, accounting for the intertemporal nature of demand, by choosing an optimal set of prices, p_t , known as the policy function. The timing of the firm's information and decisions is summarized below.

Inherits $n_{2t}, n_{3t} \rightarrow$ Chooses $p_t \rightarrow$ Observes $\bar{\epsilon} \rightarrow$ Earns π_t .

Letting V be the value function, the firm's problem can be expressed as

$$V(N_{1t}, n_{2t}, n_{3t}) = \max_{p_t} \{ \pi_t(N_{1t}, n_{2t}, n_{3t}, p_t) + \beta EV(N_{1t+1}, n_{2t+1}, n_{3t+1}) \} \quad (3.24)$$

subject to

$$\begin{aligned} N_{1t+1} &= N_{1t}(\gamma + \bar{\epsilon}), \quad |\bar{\epsilon}| < \epsilon_{\max} < \gamma, \\ n_{2t+1} &= \delta_{12}n_{1t}, \text{ and} \\ n_{3t+1} &= \delta_{23}n_{2t}, \end{aligned} \quad (3.25)$$

where

n_{1t} = the number of young smokers in period t ,

n_{2t} = the number of middle-aged smokers in period t ,

δ_{12} = percentage of young smokers who become middle-aged smokers in $t + 1$,
 δ_{23} = percentage of middle-aged who become old smokers in the next period,
 and
 ϵ_{\max} = limit of random shocks to the population growth rate to preclude the
 possibility of unrealistically large population growth.

The value of the firm today equals the profits from current decision plus the expected
 discounted value of the firm tomorrow. The solution to this stationary problem is ob-
 tained numerically by iterating its Bellman equation, equation 3.24. Since the complexity
 of these computations increases geometrically in the number of state variables, the prob-
 lem is renormalized to eliminate one state variable. Dividing through by N_{1t} and
 defining new state variables

$$x_{1t} = \frac{n_{2t}}{N_{1t}} \text{ and } x_{2t} = \frac{n_{3t}}{N_{1t}}, \quad (3.26)$$

the Bellman equation 3.24 becomes

$$\begin{aligned}
 V(x_{1t}, x_{2t}) = \max_{p_t} & (p_t - c) (\varphi(p_t) d_{1t}(p_t) + (x_{1t} + x_{2t}) d_2(p_t)) \\
 & + \beta EV(x_{1t+1}, x_{2t+1})
 \end{aligned} \quad (3.27)$$

subject to

$$\begin{aligned}
 x_{1t+1} &= \frac{\delta_{12}}{\gamma} \varphi(p_t) + \bar{\nu}_1 \geq 0, \quad \bar{\nu}_1 \in [\nu_{1 \min}, \nu_{1 \max}] \text{ and} \\
 x_{2t+1} &= \frac{\delta_{23}}{\gamma} x_{1t} + \bar{\nu}_2 \geq 0, \quad \bar{\nu}_2 \in [\nu_{2 \min}, \nu_{2 \max}]
 \end{aligned} \quad (3.28)$$

where both state variables, x_1 and x_2 , are bounded below by zero and the uncertainty in
 the transition equations arising from shocks to the population growth rate is assumed to
 be bounded.

Numerical Solution

This problem has no known analytical solution, but the value function, $V(x_1, x_2)$, and the policy function, $p_{t+1}(x_{1t}, x_{2t})$, can be solved for numerically. Since $\beta \in (0, 1)$ and the constraint set (equation 3.28) is compact and convex, equation 3.27 defines a contraction mapping for the function V . Given the concavity assumption for the profit function π and the assumptions about the stochastic shocks, \bar{v}_1 and \bar{v}_2 , there exists a unique solution to equations 3.27 and 3.28.⁸ Standard numerical dynamic programming techniques are used to compute the value and the policy functions.⁹ The state space is divided into a grid of discrete points. Starting with an initial guess for the value function V_0 , the right hand side of equation 3.27 is maximized with V_0 in place of V , subject to the constraint equations 3.28. The expectation is computed numerically by determining the transition probability for each future state, given the current state and the policy decision. The solution to this maximization problem provides the policy function, $p_0(x_1, x_2)$, that corresponds to the initial guess V_0 . Holding $p_0(x_1, x_2)$ fixed, a new value function V_1 is obtained by iterating the following equation

$$V^{i+1}(x_1, x_2) = (p_0 - c) (\varphi(p_0) d_1(p_0) + (x_1 + x_2) d_2(p_0)) + \beta E_t V^i(x_{1t+1}, x_{2t+1}). \quad (3.29)$$

Since this defines a contraction mapping, the procedure converges to the value function V_1 that corresponds to the value of following policy $p_0(x_1, x_2)$. The iteration continues until $p_0(x_1, x_2)$ and $V(x_1, x_2)$ converge to the true optimal policy function and the value function. For a given discretization, this procedure is guaranteed to converge in a finite number of steps, and for a sufficiently fine grid, this will approximate the continuous functions to arbitrary precision.

For a given set of demand functions, this algorithm calculates the value and policy functions for the model. The linear demands of equations 3.1 and 3.2 thus provide a

⁸ See Stokey and Lucas (1989), Chapter 9.

⁹ See Judd (1991) and Bertsekas (1987) for a discussion of numerical dynamic programming techniques and additional references.

Name	Variable	Value
Elastic demand:	a_1	2.4
	b_1	0.014
Inelastic demand:	a_2	1.4
	b_2	0.004
Smoking initiation rate	$\varphi(p)$	$1 - \Phi\left(\frac{p}{50}\right)$
Marginal cost	c	60
Discount factor	β	0.8
Population growth rate	γ	1.09
Survival rates:	δ_{12}	0.98
	δ_{23}	0.98
Variance of x	ν	$(0.1)^2$

Table 3.9: Parameters for Dynamic Model

back-of-the-envelope means of evaluating how price responds to variations in the age distribution in the population. Table 3.9 sets out the parameter values used in the simulation. The smoking initiation rate, $\varphi(p)$, is assumed to be $1 - \Phi(p)$, where $\Phi(p)$ is the cumulative distribution function for the standard normal distribution.

This simple dynamic model confirms our basic intuitions about expected steady state behavior of the firm. Figure 3-4 shows the firm's policy function, which determines the price to charge to maximize the firm's net present value as a function of the state variables, accounting for the stochastic nature of the problem. Again, as anticipated, the price is an increasing function of the state variables and increases more sharply for x_2 , the proportion of old smokers relative to the number of young, than for x_1 . Since old smokers die in the next period, the firm will have to lower its price in the future to attract new recruits. This means that there is less to be gained by recruiting young smokers today,

so prices are higher. Conversely, the larger proportion of middle-aged smokers, x_1 , who will survive into the next period, the higher the price will be next period and the more to be gained by attracting young smokers today. Thus the price will be lower than would be the case for a comparable increase in the proportion of older smokers.

When x_1 and x_2 are large, there are proportionately greater numbers of middle-aged and older smokers relative to the number of teenagers in the population, and the firm charges a higher price. This price increase is larger for increases in x_2 than x_1 when middle-aged and older smokers have the same price elasticity of demand. That is, increasing the proportion of older smokers leads the firm to increase its price more than for an equal increase in the fraction of middle-aged smokers.

Similar calculations can be made for a model consisting of three age cohorts – non-smoking children, teenagers initiating smoking, and adult smokers. The results show that prices increase when, other things equal, the number of nonsmoking children in the population increases. In particular, the model predicts a value for the derivative $\frac{\partial p}{\partial \left(\frac{\text{Senior}}{\text{Middle-aged}}\right)}$ of 0.05.

3.5.4 Data

The regressions used in this study require measurements for cigarette prices, excise taxes, incomes, input costs, and the age distribution of national and state populations. These data come from the Bureau of Economic Analysis, the Bureau of Labor Statistics, the Census Bureau, the Tobacco Institute, and the U.S. Department of Agriculture. Data for each of the 50 states and the District of Columbia were obtained from 1975 through 1989. Data are aggregated over populations in the nation as a whole and within each state over the period of one year. Since the states report based on a fiscal year, all state panel data are measured on a June 30 basis. Price, income, expenditure, and all other nominal variables were converted to real amounts using the Bureau of Labor Statistics national consumer price index for urban areas, CPI-U [1982-1984 = 100].

The sources of the data are discussed below for each variable.

GAUSS Tue Aug 13 15:12:26 1996

Policy Function

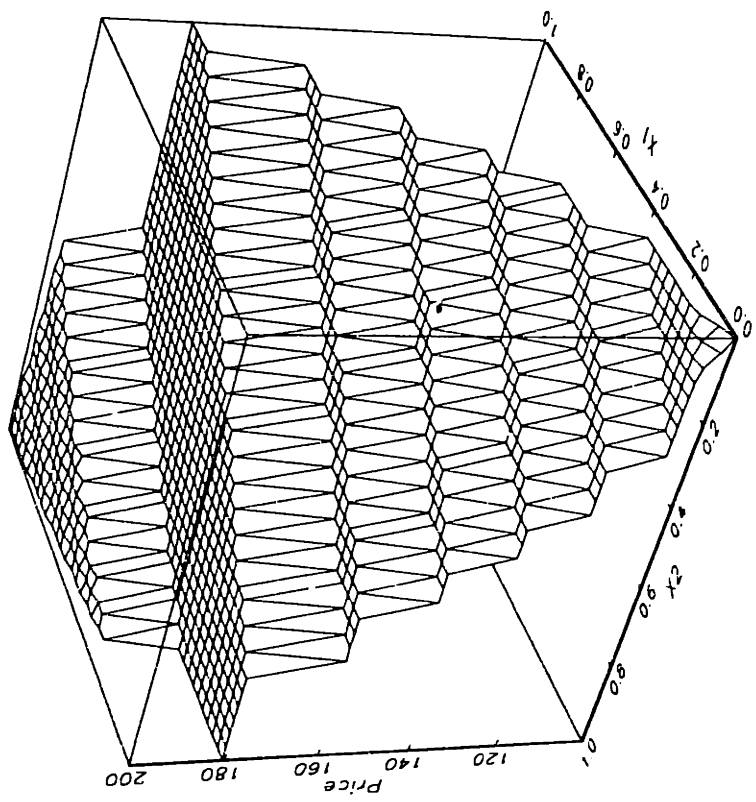


Figure 3-4: Policy Function

State retail prices. In November of each year, the Tobacco Institute surveys retail cigarette prices in each state to construct a weighted average retail price. The weights are based on the type of sale (*i.e.*, single package sold over-the-counter, carton and vending machine) and assigned based on national market shares by type of sale. The average retail prices reported by the Tobacco Institute from 1975 to 1989 do not include prices for discount or generic brands, which first appeared in the market in 1980 and are cheaper than brand name cigarettes. The unit market share of discount cigarette brands grew in an approximately linear fashion from their introduction in 1980 until 1989 when they had achieved a 15% share (Maxwell 1994).

National wholesale prices. The U.S. Department of Agriculture reports the listed, national wholesale prices for cigarettes for four categories, standard, king, filter, and 100 mm, in its publication *U.S. Tobacco Statistics* (Creek, Capehart, and Grise 1994). The national time series regressions use prices for the standard category. The wholesale price is a weighted average of wholesale prices for each category of cigarette weighted by each product's share of the total quantity manufactured. These are list, not transaction, prices exclusive of taxes.

Historically, wholesale cigarette prices have followed an unusual pattern. Manufacturers' price changes tend to be highly synchronized, typically occurring at the same time and by the same amount.

Taxes. State and federal cigarette excise taxes are reported in the Tobacco Institute's annual report, *The Tax Burden on Tobacco* (Tobacco Institute 1993). Some cities and counties, most notably New York city, impose additional excise taxes on sales within their jurisdictions. Since these have a relatively small effect on the average tax within the state, they have been ignored.

For most of the twentieth century, federal tobacco taxes were increased only to help finance U.S. military involvement or solve a budget deficit crisis. A series of wartime increases ended on November 1, 1951, during the Korean War, when the tax was raised from seven to eight cents a pack. The tax remained unchanged for the next thirty

16.8% of total advertising and promotional expenditures in 1975 to 69.9% by 1993.

Manufacturing wages. The average weekly wage for manufacturing workers was obtained from the Bureau of Labor Statistics.

PPI for tobacco leaf. The producer price index for tobacco leaf is reported by the Bureau of Labor Statistics and used as a measure of the factor input costs of cigarettes. The increasing shares of filter and low tar cigarettes, which use less tobacco, precipitated by various health issues beginning with the 1964 Surgeon General's Report has meant the amount of tobacco in cigarettes has decreased during the sample periods. Tobacco leaf represented less than 10% the retail price of cigarettes in 1992 (Goldman Sachs 1994). Since much of the tobacco crop is stored for some time before being used, costs may depend on a distributed lag of previous tobacco prices rather than just the contemporaneous price.

Chapter 4

Adolescent Exposure to Cigarette Advertising in Magazines: An Evaluation of Brand-Specific Advertising in Relation to Youth Readership

An estimated one million U.S. adolescents start smoking each year, and about half will continue to smoke into adulthood (Centers for Disease Control and Prevention 1996).¹ Nearly half of those who continue to smoke will eventually die from their cigarette use (Centers for Disease Control and Prevention 1996). The 1994 Surgeon General's report implicated the advertising and promotion of cigarettes as one cause of smoking initiation among adolescents (U.S. Department of Health and Human Services 1994). Of all the media by which cigarettes are advertised — newspapers, magazines, outdoor, and transit — magazines receive the largest share of tobacco company expenditures (Federal Trade

¹This chapter is coauthored with Michael Siegel, M.D., M.P.H., Carolyn Celebucki, Ph.D., and Gregory N. Connolly, D.M.D., M.P.H.

Commission 1996). In 1994, the tobacco industry spent \$252 million, or 46% of its total cigarette advertising budget, on advertising in magazines (Federal Trade Commission 1996).

In an effort to prevent smoking initiation by adolescents, the Food and Drug Administration (FDA) issued regulations in 1996 that restrict certain forms of cigarette advertising that are likely to appeal to adolescents (U.S. Department of Health and Human Services 1996). One of the FDA provisions restricts cigarette advertising in magazines to black text on a white background, but magazines with less than 15% youth (ages 12-17) readers and fewer than two million total youth readers are exempt from this restriction. The tobacco industry denies that its advertising targets youths, arguing that “Kids just don’t pay attention to cigarette ads, and that’s exactly as it should be” (R.J. Reynolds Tobacco Company 1984). The tobacco and advertising industries have filed suit against the FDA, charging that its regulation of cigarette advertising is unjustified and unwarranted (Teinowitz 1996).

The question of whether cigarette advertising in magazines and other media targets the youth market plays a critical role in legal and public health debates about interventions to reduce teenage smoking. This study cannot directly demonstrate an intent on the part of tobacco companies to target adolescents in their advertising because it is impossible to prove intent from correlation. What we do find is that, based on our data, youths are more heavily exposed to cigarette advertising in magazines for brands that are more popular among young smokers than for brands smoked almost exclusively by adults. While not proof of an intent to target adolescents in magazine advertisements, these findings are consistent with this hypothesis. We then argue that the other, possible explanations offered by tobacco companies for the observed correlation are not plausible, leading us to conclude that, consistent with other studies of cigarette advertising, tobacco companies may indeed target youths in their advertising.

The existing evidence that cigarette advertising in magazines targets youth readers derives primarily from studies of differences in the number or proportion of cigarette

advertisements in youth-oriented compared to adult-oriented magazines (Albright, Altman, Slater, and Maccoby (1988), Krupka, Vener, and Richmond (1990), Altman, Slater, Albright, and Maccoby (1987), Basil, Schooler, Altman, Slater, Albright, and Maccoby (1991), Freeman, Delgado, and Douglas (1993), Warner (1986), Hutchings (1981), King, Reid, Moon, and Ringold (1991)), changes in the number of ads in youth-oriented magazines over time (Albright, Altman, Slater, and Maccoby (1988), Altman, Slater, Albright, and Maccoby (1987), Basil, Schooler, Altman, Slater, Albright, and Maccoby (1991), Freeman, Delgado, and Douglas (1993), Warner and Goldenhar (1992)), demonstrations of the appeal of magazines' cigarette advertisement themes and images to youth (Huang, Burton, Howe, and Sosin (1992), Committee on Preventing Nicotine Addiction in Children and Youths (1994), Pollay and Lavack (1992)), and differences in the themes and images used in cigarette advertisements in youth-oriented and adult-oriented magazines (Altman, Slater, Albright, and Maccoby (1987), Basil, Schooler, Altman, Slater, Albright, and Maccoby (1991), King, Reid, Moon, and Ringold (1991), Warner (1985)).

Four methodological problems limit the ability of the existing studies to draw definitive conclusions. First, the demarcation between youth-oriented and adult-oriented magazines is not clear. Most, if not all, youth-oriented magazines in these studies have many more adult than youth readers. Thus, these studies cannot exclude the possibility that cigarette advertisements in these magazines are targeting adult, rather than youth readers. Magazines with high youth readership may also have many young adult readers, and the cigarette advertisements in these magazines may be targeting young adult readers (18-24 year-olds), rather than those under 18 years of age.

Second, these studies examined aggregate cigarette advertising. The inclusion of all brands, even those smoked almost exclusively by adults, in the analyses may have reduced the power of these studies to detect a significant association between cigarette advertising and youth readership, since youth tend to smoke only a few specific brands (Centers for Disease Control and Prevention 1994). If only these few brands target youth readers, examining cigarette advertising in aggregate may dilute any association that exists.

Third, the existing studies included only a small subset of all magazines, and many sampled only a portion of magazine issues during a given year. Due to the seasonal variation in advertising, a sample of issues in a given year may not reflect the nature of advertising in that magazine for the entire year. Fourth, the existing studies did not control for differences in the cost of advertising among magazines.

In this study, we examine the relationship between cigarette advertising in a given magazine and the adult and youth readerships of that magazine. This study addresses the four major limitations of previous research by: (1) using data on adult and youth magazine readership (as continuous variables) instead of classifying magazines as either adult or youth, and controlling for adult readership and young adult (ages 18-24) readership in the analysis; (2) using brand-specific, rather than aggregate, cigarette advertising data, and allowing for a differential relationship between youth readership and advertising among brands that are smoked almost exclusively by adults, compared to those smoked by a substantial proportion of youths as well; (3) collecting data on brand-specific advertising in all issues of magazines for an entire year; and (4) controlling for differences in the cost of advertising among magazines.

4.1 Methods

4.1.1 Magazine Selection

The 60 magazines with the highest overall readership for 1994 were identified using data obtained from Simmons Market Research Bureau, Inc. (Simmons Market Research Bureau, Inc. (1994a), Simmons Market Research Bureau, Inc. (1994b), Simmons Market Research Bureau, Inc. (1994c), Simmons Market Research Bureau, Inc. (1994d)) This group included all magazines with readership of greater than 1.8 million. Two criteria were used to select magazines for inclusion in the study: (1) the availability of information on adult and youth readership for 1994, and (2) the availability of information on which cigarette brands advertised in the magazine during 1994. Magazines were excluded from

the study if they did not accept tobacco advertising in 1994.

Of the 60 magazines identified, three were excluded because no information was available regarding adult (*Premiere*) or youth (*Playboy*, *Penthouse*) readership. Seven magazines were excluded because no information was available regarding tobacco advertising (*Guns and Ammunition*, *Inside Sports*, *Soap Opera Weekly*, *Hunting*, *Car Craft*, *Motorcyclist*, and *Circus*). Ten magazines were excluded because, as a policy, they did not accept tobacco advertising in 1994 (*Reader's Digest*, *National Geographic*, *Good Housekeeping*, *Muscle & Fitness*, *Seventeen*, *Teen*, *YM*, *Sassy*, *Shape*, and *Skiing*). One magazine (*Ski*) was excluded because it contained cigarette advertisements for only one brand in 1994 (Dunhill), and the other magazines in which that brand advertised were not among the 60 in our study. Thus, the final sample consisted of 39 magazines (Tables 4.1 and 4.2).

4.1.2 Data Sources

The 1994 Study of Media and Markets (Simmons Market Research Bureau, Inc. (1994a), Simmons Market Research Bureau, Inc. (1994b), Simmons Market Research Bureau, Inc. (1994c)) and 1994 Simmons Teen Age Research Study (STARS) (Simmons Market Research Bureau, Inc. 1994d) produced by the Simmons Market Research Bureau, Inc., and the Mediamark Research Inc. (MRI) Twelve Plus report (Mediamark Research Inc. 1994), produced by MRI, were used to obtain adult (ages 18 and older) and youth (ages 12-17) readership data for each magazine. Simmons Market Research Bureau and MRI are marketing research consulting firms that specialize in providing data on advertising audience size and characteristics to aid potential advertisers in marketing their products.

In addition to data on the number of adult and youth readers, we collected the following demographic information about adult readers for each magazine: median individual income; percentage of female, black, Hispanic, and young adult (ages 18 through 24) readers; percentage of readers who are smokers, heavy smokers (30 or more cigarettes per day), and smokers of menthol brands; and percentage of readers who reported a magazine to be their favorite.

Magazine	Youth Readers ¹ (millions)	Adult Readers ² (millions)	% Youth Readers	Tobacco Advertising (\$ millions)
Subject to FDA Regulations				
Better Homes and Gardens	2.0	35.1	5.5	7.0
Car and Driver	1.5	6.5	18.3	18.3
Cosmopolitan	2.3	15.5	12.8	9.4
Ebony	2.1	11.3	15.8	22.0
Elle	0.8	3.8	17.8	1.8
Entertainment Weekly	0.7	3.7	15.4	8.8
Essence	1.3	6.2	16.9	1.8
Glamour	2.2	10.7	17.1	6.0
GQ	1.0	5.8	15.1	2.0
Harper's Bazaar	0.7	3.2	18.2	1.0
Hot Rod	2.3	5.8	28.2	2.5
Jet	1.7	8.6	16.7	1.3
Life	2.7	18.0	12.9	4.7
Mademoiselle	1.4	5.6	19.7	3.1
Motor Trend	1.4	4.9	22.1	2.5
Outdoor Life	1.6	7.2	18.0	3.9
People	3.0	35.7	7.8	29.6
Popular Science	1.9	7.3	20.8	1.2
Road and Track	1.2	4.8	20.6	3.2
Rolling Stone	1.9	8.2	18.5	5.9
Self	0.8	4.1	16.2	1.1
Sport	2.3	4.5	33.8	2.4
Sporting News	1.4	3.6	27.8	1.0
Sports Illustrated	5.2	23.7	18.0	30.2
TV Guide	6.7	44.3	13.2	19.7
Vogue	2.2	10.2	18.0	3.0
Total	52.3	298.2	—	159.8
Average per Magazine	2.0	11.5	17.9	6.1

Sources: Simmons Market Research Bureau, Inc. (1994, a-d); Mediamark Research Inc. (1994); Leading National Advertisers (1994).

¹ Youth readers are defined as those ages 12-17. Adult readers are those 18 and older.

² Exempt magazines: < 2 million youth readers and < 15% youth readers, based on the 1994 data presented here.

Table 4.1: Readership Characteristics and Tobacco Advertising Expenditures in 39 Magazines, Stratified by Magazines that would be Subject to Food and Drug Administration (FDA) Tobacco Advertising Regulations – United States, 1994

Magazine	Youth Readers¹ (millions)	Adult Readers² (millions)	% Youth Readers	Tobacco Advertising (\$ millions)
Exempt from FDA Regulations				
Family Circle	1.2	27.6	4.2	6.2
Field and Stream	1.8	14.1	11.1	6.3
Ladies Home Journal	0.8	18.2	4.4	5.1
McCalls	1.3	17.7	6.7	5.0
New Woman	0.7	4.2	14.0	3.3
Newsweek	1.9	22.0	8.0	7.3
Popular Mechanics	1.6	9.5	14.5	4.5
Redbook	1.2	13.6	7.8	5.2
Soap Opera Digest	1.3	7.8	14.3	3.2
Time	2.0	23.6	7.7	12.2
True Story	0.7	4.3	14.8	1.5
Us	0.8	5.1	13.8	3.6
Woman' s Day	1.2	23.8	4.8	9.0
Total	16.5	191.6	—	72.2
Average per Magazine	1.3	14.7	9.7	5.6
Grand Total³	68.8	489.8	—	232.0
Average per Magazine³	1.8	12.6	12.3	5.9

Sources: Simmons Market Research Bureau, Inc. (1994, a-d); Mediamark Research Inc. (1994); Leading National Advertisers (1994).

¹ Youth readers are defined as those ages 12-17. Adult readers are those 18 and older.

² Exempt magazines: < 2 million youth readers and < 15% youth readers, based on the 1994 data presented here.

³ Combined results for both exempt and non-exempt magazines.

Table 4.2: Readership Characteristics and Tobacco Advertising Expenditures in 39 Magazines, Stratified by Magazines that would be Exempt from Food and Drug Administration (FDA) Tobacco Advertising Regulations – United States, 1994

From the Leading National Advertisers Brand Detail Report for 1994, we determined whether each cigarette brand advertised in each of the 39 magazines in 1994 and estimated each brand's total expenditures for advertising in the 39 magazines in 1994 (Leading National Advertisers 1994). We used the SRDS Consumer Magazine Advertising Source to obtain the cost for a single, full-page, four-color advertisement in each magazine in 1994 and the annual number of issues for each magazine (SRDS (Standard Rate and Data Service) 1997).

4.1.3 Data Collection

The data were extracted from the above publications and entered into an Excel spreadsheet. Data entry was 100%-verified by comparing printouts of the spreadsheet with the data in each publication. After verification, a SAS data set was created by converting the Excel spreadsheet using DBMS/COPY (Conceptual Software, Inc. 1994). We used SAS to conduct all analyses (SAS Institute Inc. 1994).

4.1.4 Brand Classification

We used the Center for Disease Control and Prevention's (CDC) study of cigarette brand preferences among adolescents in 1993 (Teenage Attitudes and Practices Survey - II [TAPS-II]) (Centers for Disease Control and Prevention (1994), Pollay, Siddarth, and Siegel (1996)) to divide cigarette brands into two groups: those smoked almost exclusively by adults ("adult" brands) and those smoked by a substantial proportion of adolescent smokers ("youth" brands). The TAPS-II survey collected data on tobacco use from a national household sample of adolescents by telephone interviews. The TAPS-II respondents include a cross-sectional, probability sample of 4,992 youths between the ages of 10 and 15 years and a follow-up sample of 7,960 adolescents between the ages of 15 and 22 from a previous survey (TAPS-I, conducted in 1989). To avoid possible overlap in the determination of brand preferences for youths compared to adults and to obtain nationally representative estimates, we used the cross-sectional sample of 10 to 15

year-olds to classify brands as youth or adult brands.

Details regarding TAPS-II, including the methods used to estimate brand market share, have been presented elsewhere (Centers for Disease Control and Prevention (1994), Pollay, Siddarth, and Siegel (1996)). The data used in this study were generated for use in a previous CDC study (Pollay, Siddarth, and Siegel 1996) and are based on the responses of the 70 adolescents between 10 and 15 years of age who reported that they smoked cigarettes, usually bought their own cigarettes, and usually purchased a specific cigarette brand.

Several brands were not coded individually in TAPS-II, but grouped in the categories entitled “other” or “generic”. Because 2.5% of 10 to 15 year-old smokers reported smoking a brand in the “other” category, we can infer that each of these brands individually was smoked by less than 2.5% of these smokers. But we cannot make any inferences about how far these brand market shares were below 2.5%. For this reason, we used a youth market share of 2.5% as the criterion to classify brands as either youth or adult.

We defined youth brands as the usual brand purchased by at least 2.5% of smokers aged 10 to 15 years in TAPS-II and adult brands as the usual brand smoked by less than 2.5% of 10 to 15 year-old smokers in TAPS-II. Based on this classification, the distribution of brand market shares among the 10 to 15 year-old smokers suggested a fairly clear separation of adult and youth brands: Marlboro: 42.9%, Newport: 24.6%, Camel: 13.2%, all “generic” brands: 9.3%, Kool: 4.1%, Winston: 2.8%, all “other” brands: 2.5%, Salem: 0.6%, Virginia Slims: 0%, Benson & Hedges: 0%. Approximately 9.3% of youth ages 10 to 15 reported smoking a “generic” brand. We classified generic brands as unknown, because we could not determine whether they were smoked by 2.5% or more of 10 to 15 year-old smokers.

Based on these criteria, we classified seven brands as adult brands (Salem, Virginia Slims, Benson & Hedges, Parliament, Merit, Capri, and Kent) and five brands as youth brands (Marlboro, Newport, Camel, Kool, and Winston). Smokers of the latter five brands accounted for about 88% of all 10 to 15 year-old smokers in 1993. Two generic

brands (Basic and Doral) were classified as unknown and were excluded from analyses that compared adult and youth brands.

The youth market shares referred to in this chapter are not true market shares because they do not reflect the total sales of each brand among youth smokers. Rather, we use the term “market share” to refer to the percentage, or share, of all 10 to 15 year-old smokers who smoke a particular brand. Since this definition is used consistently for all brands, it should not introduce bias into the study.

Since 1994 youth market share data were not available, the brand market share data were obtained from a 1993 survey. We do not believe this affected the classification of brands as adult or youth brands in this study, because market shares among youth change slowly and youths smoke only a few cigarette brands to any significant extent (U.S. Department of Health and Human Services (1996), Centers for Disease Control and Prevention (1994), Pollay, Siddarth, and Siegel (1996)). It is unlikely that changes in brand use among youth smokers from 1993 to 1994 would have been large enough to change the classification of brands as adult or youth brands in this study.

Although the sample size of 10 to 15 year-old smokers in TAPS-II was quite small, the brand market share estimates are consistent with estimates generated from the complete TAPS-II sample of 438 adolescent (ages 12-17) smokers (Pollay, Siddarth, and Siegel 1996). The rank order of brand preferences in the full TAPS-II sample of 12 to 17 year-olds (Marlboro: 58.5%, Newport: 14.5%, Camel: 13.3%, all generic brands: 6.4%, all other brands: 3.0%, Kool: 1.8%, Winston: 1.2%, Virginia Slims: 0.6%, Salem: 0.3%, Benson & Hedges: 0.3%) is nearly identical to the rank order among 10 to 15 year-olds. Moreover, there are no other national data on youth cigarette brand preferences in 1993 or subsequent years. Therefore, these are the best data currently available.

The final database consisted of 546 records. Each record contained a magazine name, magazine readership and advertising cost information, a cigarette brand name, and information about the brand's 1994 advertising in that magazine. There were 39 records (one record for each magazine) for each of 14 cigarette brands ($N = 546$). Of these, there

were 273 records for the adult brand group, 195 records for the youth brand group, and 78 records for the unclassified brand group.

4.1.5 Data Analysis

Overview

Our primary objectives were: (1) to examine the relationship between brand-specific cigarette advertising in magazines and youth readership, while controlling for the total readership and advertising cost per reader for each magazine, and (2) to examine differences in the relationship between advertising and youth readership for adult brands compared to youth brands.

The null hypothesis was that there is no independent relationship between the probability of a cigarette brand advertising in a magazine and the percentage of youth readers for that magazine, regardless of whether the brand is an “adult” or “youth” brand. In other words, if the target audience for cigarette brand advertising includes only adults then the presence or absence of advertising in a magazine should not be related to the percentage of youth readers (after accounting for total readership and advertising cost per reader). The main alternative hypothesis was that after controlling for total readership and advertising cost per reader, youth cigarette brands, but not adult brands, are more likely to advertise in magazines with a higher percentage of youth readership. Such a result would be expected if youth brands target youth readers in their magazine advertising.

The dependent variable in our analyses was the decision to advertise, measured as a dichotomous variable (1 if a cigarette brand advertised in a given magazine in 1994, 0 if the brand did not advertise in that magazine).

The main independent variables were the magazine’s total readership (total number of readers ages 12 and older), the magazine’s advertising cost per reader (cost of a full-page, four-color ad divided by the total number of readers), and the percentage of youth readers (number of youth readers [ages 12-17] divided by the total number of readers). Other

predictor variables that we included in the models were the total advertising expenditures among the 39 magazines for each of the 14 brands in 1994; the annual number of issues for each magazine; the median individual income of adult magazine readers; the proportion of adult readers who considered a magazine to be their favorite; and the percentage of adult readers of each magazine who were young adults (ages 18-24), female, black, Hispanic, smokers, heavy smokers, and menthol smokers.

To examine the possibility that the relationship between advertising and youth readership differs for adult and youth brands, we added interaction terms to the model. These variables allowed us to estimate separate regression coefficients for youth and adult brands. For example, an interaction variable for youth readership was defined as $(dummy)(percentage\ youth\ readers)$, where dummy is 0 for adult brands and 1 for youth brands. This variable, which we will refer to as the youth readership interaction variable, assessed whether the relationship between advertising intensity and youth readership differed for youth and adult brands. A regression coefficient of zero for this interaction variable would indicate that no significant difference exists between adult and youth brands in the relationship between advertising and youth readership.

Similarly, we developed interaction terms for the median income of magazine readers, the percentage of young adult (ages 18-24) readers, female readers, black readers, Hispanic readers, smokers, heavy smokers, and menthol smokers for each magazine, and the percentage of readers who reported that a magazine was their favorite. For example, the interaction term for percentage of young adult readers was $(dummy)(percentage\ young\ adult\ readers)$, where dummy is 0 for adult brands and 1 for youth brands. We also included a dummy term, allowing adult and youth brands to have different intercepts.

Several of the predictor variables were strongly correlated. To explore potential multicollinearity problems (Hosmer and Lemeshow (1989), McDaniel (1981), Neter and Wasserman (1974)), we controlled for each possible confounder in a separate regression model. The basic model included as predictor variables total readership, advertising cost per reader, the total advertising budget for each cigarette brand, the annual number of

issues for each magazine, percentage youth readership, and the youth readership interaction term. Additional models added one of the following variables and its corresponding interaction term: percentage of young adult, black, female, or Hispanic readers, percentage of readers who reported that a magazine was their favorite, or the percentage of smokers, heavy smokers, or menthol smokers among each magazine's adult readership. Finally, we ran a regression model that simultaneously controlled for all of these independent variables.

Since the criteria used to classify brands as adult or youth could affect the results, we repeated the analyses using a more stringent criterion for the definition of a youth brand: youth market share greater than 10%. Using this criterion, there were three youth brands (Marlboro, Camel, and Newport). The remaining 11 brands were classified as adult brands since their youth market shares were below 10%.

Logistic Regression Analysis

We conducted multiple logistic regression analyses to examine the relationship between magazine readership characteristics and the presence or absence of brand-specific advertising in a given magazine. Our basic model was:

$$\ln\left(\frac{P}{1-P}\right) = A + A_i(\text{dummy}) + B(\text{total number of readers}) \\ + C(\text{advertising cost per reader}) \\ + D(\text{total advertising expenditures for brand among all 39 magazines}) \\ + E(\text{number of annual issues of magazine}) \\ + F(\text{percentage of youth readers}) \\ + F_i(\text{dummy})(\text{percentage of youth readers}) \\ + \text{error,}$$

where P is the probability that a brand will advertise in a given magazine, and *dummy* is 0 for adult brands and 1 for youth brands.

These models assess the relationship between advertising and youth readership separately for adult and youth brands. For adult brands, the odds ratio that reflects the difference in a brand's likelihood of advertising in a magazine per one percentage point increase in a magazine's youth readership is e^F . The corresponding odds ratio for youth brands is $e^{(F+F_i)}$. Thus, if the coefficient, F_i , for the interaction variable is 0, there is no difference in the relationship between advertising and youth readership for adult and youth brands.

Under the null hypothesis that neither adult nor youth brands target youth readers, the coefficients F and F_i would both be 0 (the odds ratios for both adult and youth brands would be 1.0). Under the main alternative hypothesis (that youth brands alone are more likely to advertise in magazines with a higher percentage of youth readers), the coefficient F would be 0 (odds ratio for adult brands would be 1.0) and the coefficient F_i would be positive (odds ratio for youth brands would be greater than 1.0).

To facilitate interpretation of the results of our models, we present an adjusted odds ratio that reflects the difference in the likelihood of advertising in a magazine for each 10% (10 percentage point) increase in youth or other demographic group readership, for each increase of 10 million in the total number of readers, for each increase of \$10,000 in the cost of reaching one million readers with a full-page, four-color advertisement, for each increase of 10 in the annual number of magazine issues, for each increase of \$10,000 in median individual income of magazine readers, and for each increase of \$10 million in a brand's total advertising budget for the 39 magazines. Since the distribution of percentage youth readership ranged from about 4% to 34%, a 10 percentage point increase in youth readership represents about one-third of this range. Presenting the odds ratio for this magnitude of change in the percentage of youth readers for a magazine allows an interpretation of the practical meaning of the regression coefficients. The magnitude of the difference in levels of the other variables that we used to present odds ratios were chosen with a similar rationale.

To assess whether the inclusion of each interaction term significantly improved the

overall model, we used the likelihood ratio test, which compares the log likelihood of the models with and without the variable of interest (Hosmer and Lemeshow 1989). A Wald test was conducted to assess the significance of the regression coefficients (Hosmer and Lemeshow 1989). Confidence intervals for these odds ratios were calculated using asymptotic standard errors estimated in the regression models (Hosmer and Lemeshow 1989).

Brand-Specific Analyses

To generate brand-specific estimates of the relationship between advertising and youth readership, we ran the logistic regression models using a separate intercept term and a separate youth readership interaction term for each cigarette brand. This allowed us to estimate the effect of youth readership on advertising for each of the cigarette brands separately. This model avoids the potential problem of defining what constitutes a youth or an adult cigarette brand.

4.2 Results

4.2.1 Descriptive Analysis

The 39 magazines in this study accepted \$4.1 billion in total advertising in 1994, of which tobacco advertisements accounted for \$232.0 million (5.7%) (Tables 4.1 and 4.2) and cigarette advertisements accounted for \$207.1 million (5.1%). The proportion of total advertising revenues represented by tobacco ranged from 1.7% (*Harper's Bazaar*) to 22.9% (*True Story*). There were 51,579 pages of total advertising in these magazines, of which 2,737 (5.3%) were cigarette advertisements. These cigarette advertisements represented 2,085 separate insertions.

Average youth readership ranged from 674,000 (*Entertainment Weekly*) to 6.7 million (*TV Guide*) and the proportion of total readership made up of youths ranged from 4.2% (*Family Circle*) to 33.8% (*Sport*) (Tables 4.1 and 4.2). There were 11 magazines with

greater than two million youth readers, 21 with greater than 15% youth readership, and 26 meeting either one or both of these conditions. These 26 magazines meet the criteria for regulation of cigarette advertising by FDA. The remaining 13 magazines would be exempt from FDA regulation.

The total youth readership, ignoring audience duplication, of the 13 magazines exempt from FDA regulation based on our data was 16.5 million, and the total tobacco advertising expenditures in these magazines for 1994 was \$72.2 million (Tables 4.1 and 4.2). The average number of youth readers was 2.0 million for magazines that would be subject to FDA regulation based on these readership data and 1.3 million for magazines that would be exempt from FDA regulation. The average amount spent for tobacco advertising per magazine was \$6.1 million for the group that would be subject to FDA regulation and \$5.6 million for the group that would be exempt.

4.2.2 Logistic Regression Analysis

The likelihood of advertising in a magazine increased significantly with increases in the number of annual issues of a magazine and with increases in the total advertising budget for a cigarette brand. For each increase of \$10,000 in a brand's magazine advertising budget, the odds of that brand advertising in a given magazine increased by a factor of 1.7 (OR = 1.72, 95% CI [1.44-2.06]) (Table 4.3). For each increase of 10 in the number of annual issues for a magazine, the odds of a brand advertising in that magazine increased by a factor of 1.2 (OR = 1.18, 95% CI [1.01-1.39]).

After accounting for each magazine's total readership, advertising cost per reader, and annual number of issues, and for each cigarette brand's total advertising budget for the 39 magazines, the odds of an adult brand advertising in a magazine decreased by a factor of 0.4 (OR = 0.39, 95% CI [0.24-0.65]) for each 10% (10 percentage point) increase in the percentage of youth readers (Table 4.3). For youth brands, the odds of advertising in a magazine increased by a factor of 3.8 for each 10% increase in the percentage of youth readers (OR = 3.79, 95% CI [1.98-7.26]). The addition of the youth readership variables

	Adult Brands ¹	Youth Brands ¹
Youth Brands Defined as Those Smoked by \geq 2.5% of 10–15 Year-Old Smokers		
Total magazine readership	0.97 (0.72-1.31)	
Cost per page/100 magazine readers	0.50 (0.21-1.19)	
Total advertising budget for brand	1.72 (1.44-2.06)	
Annual issues of magazine	1.18 (1.01-1.39)	
% Youth readers	0.39 (0.24-0.65)	3.79² (1.98-7.26)
Youth Brands Defined as Those Smoked by \geq 10% of 10–15 Year-Old Smokers		
Total magazine readership	1.04 (0.79-1.37)	
Cost per page/100 magazine readers	0.56 (0.25-1.23)	
Total advertising budget for brand	1.91 (1.61-2.28)	
Annual issues of magazine	1.17 (1.01-1.35)	
% Youth readers	0.76 (0.52-1.12)	3.31² (1.52-7.21)

All estimates are adjusted for variables shown. Changes in the odds that a brand is advertised in a magazine are presented for an increase of 10 million in total readership, an increase of \$10,000 in the cost of reaching one million readers with a full-page, four-color advertisement, an increase of \$10 million in a brand's total advertising budget, an increase of 10 in the number of annual issues of a magazine, and an increase of 10 percentage points in the proportion of magazine readers who are youths (ages 12-17).

¹ Youth brands are those smoked by \geq 2.5% (top half of table) or \geq 10% (bottom half of table) of 10–15 year-old smokers in the 1993 Teenage Attitudes and Practices Survey – II.

Adult brands are those smoked by $<$ 2.5% or $<$ 10% of 10-15 year-old smokers in 1993.

² Significant difference ($p < 0.05$) in the relationship between advertising and the variable of interest for adult brands compared to youth brands (t -test for significance of the interaction term for that variable in the regression model).

Table 4.3: Adjusted Odds Ratios (95% Confidence Intervals) for the Change in the Likelihood of a Cigarette Brand Advertising in a Magazine Associated with Changes in the Percentage of Youth (Ages 12-17) Readers and Other Brand and Magazine Characteristics, 1994

significantly improved the model ($p = 0.0001$ for likelihood ratio test), and the coefficient for the youth readership interaction term was significant ($p = 0.0001$), indicating that the relationship between advertising and youth readership was significantly different for adult and youth brands.

To check the assumption of linearity of the log odds of advertising in a magazine with percentage youth readership, we plotted the log odds of a brand advertising in a magazine for each quartile of percentage of youth readership against the mid-point of percentage youth readership for that quartile. For adult brands, the logits were 0.22, 0.11, -0.17, and -1.00 for the midpoints 6.0, 11.5, 16.7, and 25.9. This relationship was quite linear ($r = 0.97$). For youth brands, the logits were 0.03, 0.33, 0.62, and 0.94 for the midpoints 9.1, 16.0, 19.3, and 27.3. This relationship was also quite linear ($r = 0.99$).

We examined the fit of the logistic regression model by comparing predicted probabilities of advertising in a magazine with the observed responses. Approximately 75% of the observations were correctly predicted by the regression model.

We explored the possibility that the observed results were due to the influence of data from a single brand by repeating the analyses with data for one brand at a time excluded from the analysis. In each case, there was still a statistically significant difference between adult and youth brands in the relationship between advertising and youth readership, with adult brands being significantly less likely, and youth brands being significantly more likely, to advertise in magazines with a higher percentage of youth readers.

We examined the effect of redefining youth brands as those with greater than 10% market share among 10 to 15 year-old smokers (Marlboro, Newport, and Camel). For these three brands, the odds of advertising in a magazine increased by a factor of 3.3 for each 10% increase in youth readership (OR = 3.31, 95% CI [1.52-7.21]) (Table 4.3). For all other brands, the odds of advertising in a magazine decreased by a factor of 0.8 for each 10% increase in youth readership (OR = 0.76, 95% CI [0.52-1.12]). The difference in the relationship between advertising and youth readership was again statistically significant for adult and youth brands ($p = 0.0004$).

To rule out the possibility that the observed findings were due to errors in classification of brands for which youth market share data were not available, we repeated the analysis without data for these brands. Restricting the analysis to the eight brands for which the youth market share was known (Table 4.5) did not affect the results.

After controlling for the percentage of young adult readers in each magazine, the relationship between advertising and youth readership still differed significantly for adult and youth brands ($p = 0.0001$) (Table 4.4). For adult brands, a higher percentage of young adult readers in a magazine significantly increased the odds of advertising in that magazine, while a higher percentage of youth readers significantly decreased the odds of advertising in that magazine. For each 10% increase in the percentage of young adult readers, the odds of advertising in a magazine increased by a factor of 2.1 (OR = 2.14, 95% CI [1.38-3.32]) (Table 4.4). For each increase of 10% in youth readership, the odds of advertising in a magazine decreased by a factor of 0.2 (OR = 0.18, 95% CI [0.09-0.38]).

Youth brands were more likely to advertise in magazines with greater young adult readership. Unlike adult brands, they were also more likely to advertise in magazines with higher youth readership. The odds of a youth brand advertising in a magazine increased by a factor of 1.9 (OR = 1.86, 95% CI [1.10-3.16]) for each 10% increase in young adult readership, and by a factor of 2.1 (OR = 2.10, 95% CI [0.94-4.69]) for each 10% increase in youth readership (Table 4.4).

We explored the effects of adding other predictor variables to the logistic models (Table 4.4). For adult brands, the likelihood of advertising in a magazine increased significantly with a higher percentage of female readers and Hispanic readers, and decreased significantly with a higher percentage of readers who are heavy smokers, readers for whom a magazine is their favorite, and readers with higher income. For youth brands, the likelihood of advertising in a magazine decreased significantly with the proportion of magazine readers who consider a magazine to be their favorite and with the percentage of black readers.

For both adult and youth brands, controlling for the predictor variables did not

Control Variable	Odds Ratio (OR) for Control Variable	OR for % Youth Readers
Adult Brands		
% Young adult readers	2.14 (1.38-3.32)	0.18 (0.09-0.38)
% Female readers	1.30 (1.17-1.44)	0.85 (0.46-1.57)
% Black readers	1.03 (0.91-1.17)	0.38 (0.23-0.64)
% Hispanic readers	3.88 (1.67-9.04)	0.29 (0.17-0.50)
% Smokers	0.62 (0.30-1.29)	0.40 (0.24-0.66)
% Heavy smokers	0.02 (0.00-0.20)	0.46 (0.27-0.77)
% Menthol smokers	1.02 (0.40-2.58)	0.39 (0.23-0.64)
% Favorite magazine	0.66 (0.46-0.93)	0.39 (0.23-0.64)
Median income of readers	0.17 (0.07-0.37)	0.48 (0.28-0.82)
All variables included		0.47 (0.18-1.23)
Youth Brands		
% Young adult readers	1.86 (1.10-3.16)	2.10 (0.94-4.69)
% Female readers	0.96 (0.85-1.07)	3.95 (1.87-8.34)
% Black readers	0.86 (0.73-1.00)	4.25 (2.16-8.37)
% Hispanic readers	1.78 (0.66-4.81)	3.30 (1.67-6.53)
% Smokers	1.21 (0.51-2.90)	3.80 (1.97-7.32)
% Heavy smokers	4.52 (0.34-59.4)	3.76 (1.91-7.40)
% Menthol smokers	0.47 (0.15-1.46)	4.05 (2.07-7.92)
% Favorite magazine	0.53 (0.34-0.80)	4.28 (2.15-8.53)
Median income of readers	0.61 (0.08-1.57)	4.26 (2.20-8.26)
All variables included		3.19 (0.85-12.0)

Each line presents the results of adding the variable shown to a model that includes total readership, advertising cost per reader, total advertising budget for brand, number of annual magazine issues, percentage of youth readers, and the youth readership interaction term. Changes in the odds of advertising in a magazine associated with changes in youth readership and other demographic characteristics are presented per increase of 10 percentage points in the proportion of magazine readers in that demographic group. Changes in the odds of advertising associated with changes in income are presented per increase of \$10,000 in the median individual income of adult magazine readers.

Table 4.4: Adjusted Odds Ratios (95% Confidence Intervals) for the Change in the Likelihood of a Cigarette Brand Advertising in a Magazine Associated with Changes in the Percentage of Youth (Ages 12–17) Readers, Controlling for Demographic Characteristics of Magazine Readers, 1994

	Young Adolescent (Ages 10-15) Market Share (%)	Youth (Ages 12-17) Market Share (%)	Odds Ratio for Percentage of Youth Readers
Youth Brands			
Marlboro	42.9	58.5	2.91
Newport	24.6	14.5	3.09
Camel	13.2	13.3	4.07
Kool	4.1	1.8	4.76
Winston	2.8	1.2	9.38
All Youth Brands	87.6	89.3	3.79 (1.98-7.26)
Adult Brands			
Salem	0.6	0.3	2.41
Virginia Slims	0	0.6	0.04
Benson and Hedges	0	0.3	0.17
Capri	< 2.5	< 3.0	0.39
Kent	< 2.5	< 3.0	0.19
Merit	< 2.5	< 3.0	0.03
Parliament	< 2.5	< 3.0	1.31
All Adult Brands	0.6	1.2	0.39 (0.24-0.65)
All Cigarette Brands	88.2	90.5	0.99 (0.69-1.41)

All estimates are adjusted for total readership, advertising cost per reader, total advertising budget for brand, and annual number of magazine issues. Changes in the odds of a brand advertising in a magazine are presented per increase of 10 percentage points in the proportion of magazine readers who are youth (ages 12-17). Estimates for all youth brands, all adult brands, and all brands combined are presented with 95% confidence intervals in parentheses. The proportion of 10-15 year-old and 12-17 year-old smokers who smoke that cigarette brand is from Teenage Attitudes and Practices Survey – II. The proportion of smokers for brands not reported in the Teenage Attitudes and Practices Survey – II is listed as < 2.5% for “other” brands, and < 9.3% for “generic” brands (see text for explanation).

Table 4.5: Adjusted Odds Ratios for the Change in the Likelihood of a Cigarette Brand Advertising in a Magazine Associated with Changes in the Percentage of Youth (Ages 12–17) Readers — by Brand, 1994

substantially affect the odds ratios for differences in the likelihood of advertising in a magazine associated with changes in youth readership. For adult brands, the odds ratios were less than 1.0 in all models (range, 0.18-0.85) (Table 4.4). For youth brands, the odds ratios were greater than 1.0 in all models (range, 2.10-4.28). The relationship between advertising and youth readership was significantly different for adult and youth brands in all models, including one that controlled simultaneously for all independent variables.

Brand-Specific Analyses

The likelihood of advertising in a magazine increased with higher youth readership for all five youth brands and decreased with higher youth readership for five of the seven adult brands (Table 4.5). There was a complete separation of adult and youth brands: the odds ratios for youth brands were all higher than 2.9, while the odds ratios for adult brands were all lower than 2.5.

4.3 Discussion

To the best of our knowledge, this chapter is the first to examine systematically the relationship between cigarette brand-specific advertising and youth readership among a large, nearly complete sample of the most highly-read magazines over a full year. It is also the first study of cigarette advertising in magazines to allow for a differential effect for brands that are smoked by young adolescents compared to those smoked almost exclusively by adults. After controlling for the total number of readers and cost of advertising in each magazine, we found that youth brands were more likely to be advertised in magazines with a higher percentage of youth (ages 12-17) readers, while adult brands were less likely to advertise in magazines with a higher percentage of youth readers. This suggests that youth brands may preferentially advertise in magazines with higher proportions of youth readers.

To explain the observed brand-specific relationship between advertising and youth

readership, a potential confounding variable would have to be positively correlated with youth readership, positively correlated with advertising among youth brands, and negatively correlated with advertising among adult brands (or the reverse, all the above correlations could be in the opposite direction). Of the many potential confounding variables we considered, only two met these criteria: female readership and young adult readership.

After controlling for female readership, however, we still found a significantly different relationship between advertising and youth readership for youth and adult brands, and youth brands were still significantly more likely to advertise in magazines with increased youth readership. Controlling for female readership reduced the magnitude and eliminated the statistical significance of the negative association between advertising and youth readership for adult brands. It is quite possible that adult brands are more interested than youth brands in reaching female readers. Magazines with a higher proportion of female readers also have a lower percentage of youth readers, which could explain why adult brands are less likely to advertise in magazines with higher youth readership.

Young adult readership is another potential confounder of the observed relationship between advertising and youth readership. The percentages of youth readers and young adult readers were highly correlated ($r = +0.68$). Young adult readership was negatively correlated with advertising among adult brands and positively correlated with advertising among youth brands. Controlling for young adult readership reduced the magnitude of the association between advertising and youth readership for youth brands, but the association was still statistically significant at the 90% significance level.

Our findings do not support the hypothesis that youth cigarette brands are marketed only to young adult, and not youth, magazine readers. If this hypothesis were true, one would expect youth brands to be more likely than adult brands to advertise in magazines with a higher percentage of young adult readers. We found no significant difference between youth and adult brands in the relationship between advertising and young adult readership. The probability of advertising in a magazine increased by a similar amount

for youth and adult brands.

Further, the finding of a significant difference between youth and adult brands in the relationship between advertising and youth readership was not explained by differences in the proportion of young adult readers for different magazines. This difference remained significant after controlling for all independent variables in the model, both individually and simultaneously.

There are also theoretical reasons why the likelihood is small that our observed findings are due to targeting of young adults by the brands that are smoked most by youth. Because only 5% of regular smokers start smoking after age 24 (U.S. Department of Health and Human Services 1994), it is unlikely that any cigarette brand would not preferentially advertise in magazines with a higher proportion of young adult readers. Rates of brand switching are highest among the 18 to 24 year-old group and decrease with age (Siegel, Nelson, Peddicord, Giovino, and Eriksen 1996). Even if adult brands were merely trying to encourage brand switching and maintain market share, there would still be an economic incentive to reach young adults with their brand-specific advertising messages.

The tobacco industry has long recognized the importance of the 18 to 24 year-old market, which it refers to as “young adult smokers” (U.S. Department of Health and Human Services 1996). As reported in the FDA rule, tobacco industry documents stated that “No more than 5% of smokers start after age 24 . . . Although 18- to 24-year-olds account for a very small part of market share, this age group represents the future of a brand. Those young, brand loyal smokers who now consume very few cigarettes, will consume more cigarettes with age and generally remain loyal to this first brand, its brand family or to the company” (U.S. Department of Health and Human Services 1996).

The economic incentive for targeting youths and young adults has been demonstrated empirically in other studies. Brand loyalty is usually established with the first cigarette smoked (DiFranza, Eddy, Brown, Ryan, and Bogojavlensky 1994). Of all adolescent smokers, 67% report that the first brand they smoked regularly was the same brand as their first cigarette (DiFranza, Eddy, Brown, Ryan, and Bogojavlensky 1994). Moreover,

youth brand preference has recently been shown to be associated not only with brand use decisions, but with the initiation and maintenance of cigarette smoking (Volk, Edwards, Lewis, and Schulenberg 1996).

The findings of this study are not explained by other predictor variables, including the median income, race/ethnicity, or smoking behavior of magazine readers. These findings also do not depend upon the criteria used to classify youth brands and adult brands. Using more conservative criteria that limited the youth brand category to the three top brands did not affect the results, and there was a nearly complete separation of the youth and adult brands when regression coefficients were estimated for each brand separately. In addition, the findings did not change when the analysis was restricted to brands with a known youth market share, or when data for one brand at a time was excluded from the analysis.

There are several important limitations to this study. First, although it is unlikely that our findings are explained entirely by the hypothesis that youth cigarette brands are targeting young adults, rather than adolescents, in their advertising, it is probable that some of the observed effect of youth readership is due to targeting of young adults. The presence of multicollinearity between youth and young adult readership among magazines in this study makes it difficult to estimate accurately the degree to which brands are targeting youth compared to young adult readers.

Second, the study does not allow us to make inferences regarding the potential role of cigarette advertising in magazines on smoking behavior, including smoking initiation, among adolescents. Third, it is impossible to demonstrate an intent to target youth from an analytic study such as this one, even though the data indicate a brand-specific relationship between advertising and youth readership.

Fourth, although this study provides a quantitative examination of the relationship between cigarette brand advertising and youth readership, it does not provide information on the qualitative aspects of these cigarette ads, the advertising themes and images and their potential appeal to youth, or the relationship between the advertising themes and

images and the characteristics of magazine readers.

Despite these limitations, when considered together with the results of previous studies on the content of cigarette advertising in magazines (Huang, Burton, Howe, and Sosin (1992), Committee on Preventing Nicotine Addiction in Children and Youths (1994), Pollay and Lavack (1992)), the quantity and nature of cigarette ads in different types of magazines (Albright, Altman, Slater, and Maccoby (1988), Krupka, Vener, and Richmond (1990), Altman, Slater, Albright, and Maccoby (1987), Basil, Schooler, Altman, Slater, Albright, and Maccoby (1991), Freeman, Delgado, and Douglas (1993), Warner (1986), King, Reid, Moon, and Ringold (1991), King, Reid, Moon, and Ringold (1991), Warner (1985)), the changes in cigarette advertising over time (Albright, Altman, Slater, and Maccoby (1988), Altman, Slater, Albright, and Maccoby (1987), Basil, Schooler, Altman, Slater, Albright, and Maccoby (1991), Freeman, Delgado, and Douglas (1993), Warner and Goldenhar (1992)), and the statements regarding marketing cigarettes to youths and young adults that were revealed in internal tobacco industry documents (U.S. Department of Health and Human Services (1994), U.S. Department of Health and Human Services (1996), Pollay and Lavack (1992), Pollay, Siddarth, and Siegel (1996), Glantz, Slade, Bero, Hanaeuer, and Barnes (1996), Hilts (1996), Gostin, Arno, and Brandt (1997), Schwartz (1995), Kwechansky Marketing Research (1982)), our findings provide additional new evidence that cigarette advertising in magazines may target a youth audience. Moreover, regardless of intent, the data show that youths are more heavily exposed to magazine cigarette advertisements for brands that are popular among youth smokers than for brands smoked almost exclusively by adults.

Our finding that there is no substantial difference in the percentage of youth readers among magazines that are subject to, or exempt from, FDA regulation suggests that the distinction made by FDA between “youth” and “adult” magazines is not justified on public health grounds. The estimated overlap in youth readers between exempt and non-exempt magazines is substantial. Regulating only a subset of magazines is therefore unlikely to be effective in eliminating or significantly reducing youth exposure to cigarette

advertising.

This study has important public health policy implications. By adding to the evidence that cigarette advertising in magazines targets youth, the results of this study strengthen the justification for regulating cigarette advertising in magazines. Our findings also suggest that there is no effective approach that will prevent significant youth exposure to cigarette advertising in magazines short of eliminating the advertising altogether. Based on our documentation of widespread and heavy exposure of youth to cigarette advertising in magazines, public health considerations argue that cigarette advertising in all magazines should be eliminated.

Chapter 5

Estimating the Elasticity of Demand and Cross-Border Effect of Cigarette Sales in New England States

Cigarette excise taxes make significant contributions to tax revenues and play an important role in public health policy in the United States and abroad. At the heart of the separate but related debates on the advantages of raising revenue through cigarette excise taxes and of using them as an instrument of public health policy lies the question of how consumers respond to changes in cigarette prices and their incomes. Any analysis of these issues depends crucially on accurate estimates of key parameters governing cigarette demand, but estimates for the price and income elasticities of demand for cigarettes vary considerably. These discrepancies may be attributable to differences in data (time series, cross-section, and micro-based) and estimation techniques, including a variety of underlying economic models, some of which attempt to model cigarette addiction.¹ One factor that may account for some of these differences has not been adequately studied: the role of cross-border effects.

¹Wasserman, Manning, Newhouse, and Winkler (1991) provide a recent and cogent review of the prior cigarette demand studies.

Several studies have found small, but statistically significant, shifts in per capita cigarette sales attributed to price differences between states (*see, inter alia*, Baltagi and Levin (1986); Keeler, Hu, Barnett, and Manning (1993); Wasserman, Manning, Newhouse, and Winkler (1991)).² Cross-border effects arise from three different economic activities: cross-border shopping, smuggling and tourism. Cross-border shopping is a complex phenomenon that depends on the price of cigarettes in one state relative to adjacent states, the populations near state borders since these residents are the most likely potential out-of-state consumers, and the costs, principally transportation, of cross-border activities. Differences in costs also drive smuggling of cigarettes to evade high excise taxes. Cigarettes smuggled from Virginia, or another of the low excise tax states, avoid the higher cigarette taxes imposed by the New England states.³ Others have attempted to estimate the importance of smuggling to potential revenue losses by including the cigarette excise tax of a low tax state as a variable in the consumption equation, but this study does not consider the potential effect of smuggling. Finally, cigarettes consumed by residents of one state while visiting another also contribute a cross-border effect, but unlike other cross-border transactions, net cigarette consumption by tourists is assumed, for the purpose of this analysis, to be unresponsive to changes in either the excise tax or the price of cigarettes.

The cross-border effects investigated in this study pertain only to out-of-state shop-

²Baltagi and Levin (1986) calculate, as an example, the effect of a 10% cigarette tax increase in Massachusetts on consumption in New Hampshire based on the results from a pooled regression. Within the limitations of the data, their results accord with those of this study.

Chaloupka (1991) considers the effect of doubling the federal excise tax rate, as then proposed as part of the deficit reduction package, on average cigarette consumption. He also notes that Harris (1987) suggests that the price increase following a federal tax increase could be much greater than the tax increase. Examining evidence from the 1983 federal tax increase, Harris argues that producers used the federal tax increase as a coordinating mechanism for an oligopolistic price increase.

Trigg and Bosanquet (1992) simulate the possible impacts of European tax harmonization in the context of rising incomes. The authors conclude that a much more ambitious strategy is needed if smoking rates are to be significantly reduced in accordance with the stated aim of the World Health Organization.

³As of January 1, 1993, the cigarette excises taxes in the tobacco producing states were 7¢ or less (Kentucky 3¢, North Carolina 5¢, South Carolina 7¢ and Virginia 2.5¢) while those in the New England states considered ranged from 20¢ to 51¢ (Connecticut 45¢, Massachusetts 51¢, New Hampshire 25¢, Rhode Island 37¢, and Vermont 20¢).

ping. Because of its small size, easy access to nearby states, high population densities, and divergent state cigarette excise taxes, New England provides an ideal laboratory for examining the role cross-border shopping plays in cigarette consumption.

This chapter makes two contributions to the existing literature on cigarette demand. First, cross-border effects are incorporated in an econometric model that allows for a separate effect from each adjacent state.⁴ Second, it applies an econometric technique not previously used in cigarette demand studies, the seemingly unrelated regression model (SUR), to estimate individual state effects while allowing for individual serial correlation and contemporaneous correlation among the errors.

Using annual time series data from 1958 to 1992, this study estimates the long-run price and income elasticities of demand for cigarettes and examines the importance of cross-border transactions for New England states. Cross-border effects are found to be statistically significant factors affecting per capita cigarette sales in New Hampshire, Rhode Island, and Vermont. The response of cigarette sales to differences in prices, including cigarette excise taxes, implies that these states do not have full control over their own tax bases and that each state, in deciding its own public health and revenue policies, must incorporate prices and tax rates in neighboring jurisdictions.

The remainder of this chapter contains five sections. Section I summarizes per capita cigarette sales in New England and introduces the theoretical and empirical issues pertaining to estimating aggregate cigarette demand. Section II describes the specification and methodology used to estimate price and income elasticities for cigarettes and to test the significance of cross-border effects among the New England states. Section III reviews the data, and section IV presents the main empirical results. Finally, section V summarizes the conclusions of the research and their implications for state tax and public health policies.

⁴All previous studies use either a weighted average or minimum price among neighboring states. Thus one cannot identify which state or states contribute to the cross-border effect nor can one account for demographic or geographic factors.

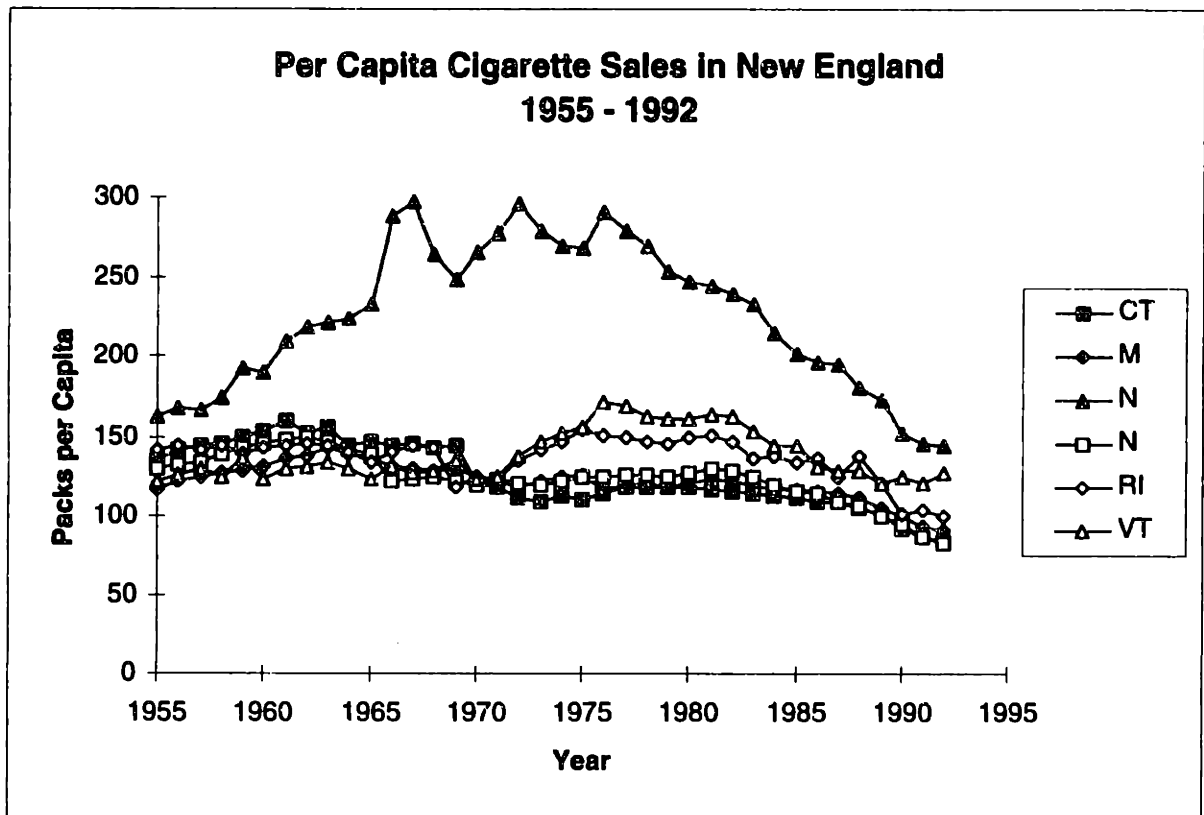


Figure 5-1: Cigarette Sales in New England, 1955 – 1992

5.1 Cigarette Sales in New England

Because of their small size, easy access to adjacent states, and different cigarette excise tax rates, the New England states offer an ideal situation to probe the significance of cross-border effects on cigarette sales. Consider the graph in Figure 5-1, summarizing per capita cigarette sales in Massachusetts and adjacent states from 1955 to 1992. During the 1980s, New Hampshire, Rhode Island, and Vermont had the lowest state excise tax rates, the lowest retail cigarette prices, and the highest per capita sales, as shown in Figures 5-1, 5-2, and 5-3. The case of New Hampshire, where per capita sales have been as high as twice that of any other New England state, is particularly striking and suggests that cross-border effects are important.

Simultaneity, serial correlation and multicollinearity are the classic pitfalls in estimat-

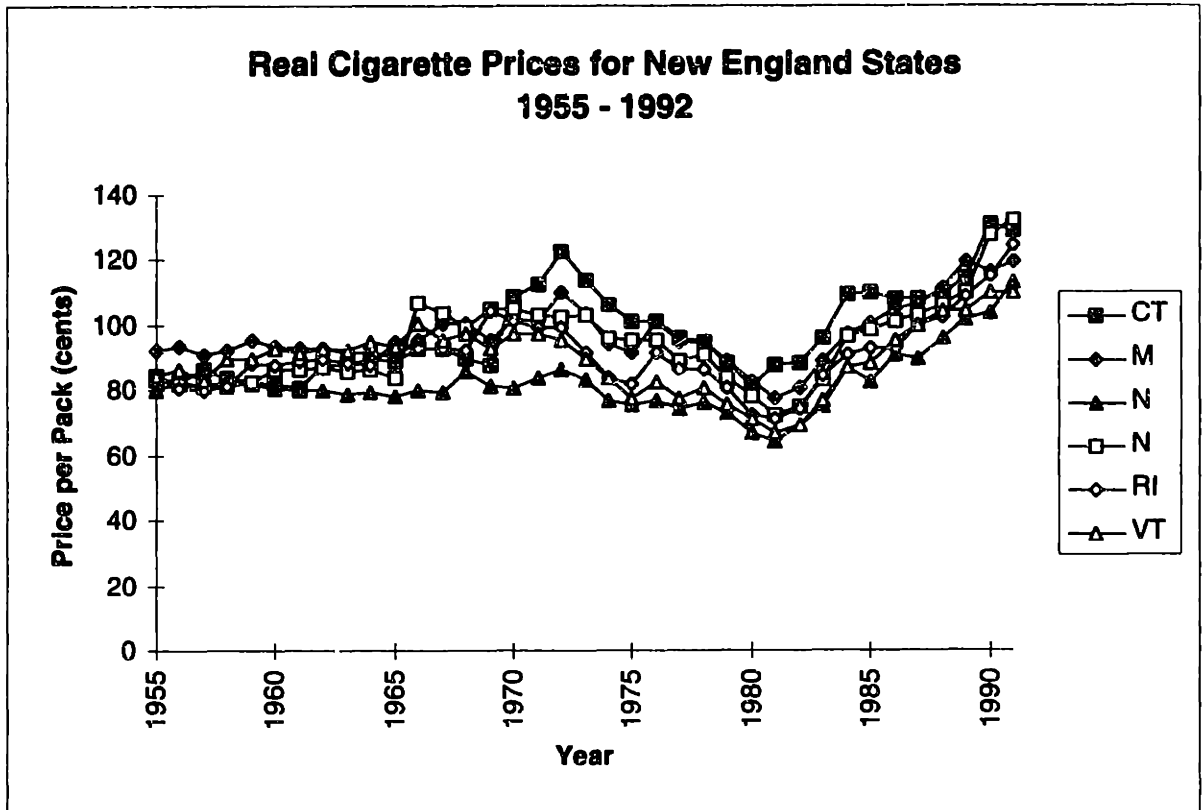


Figure 5-2: Real Cigarette Prices in New England, 1955 – 1992

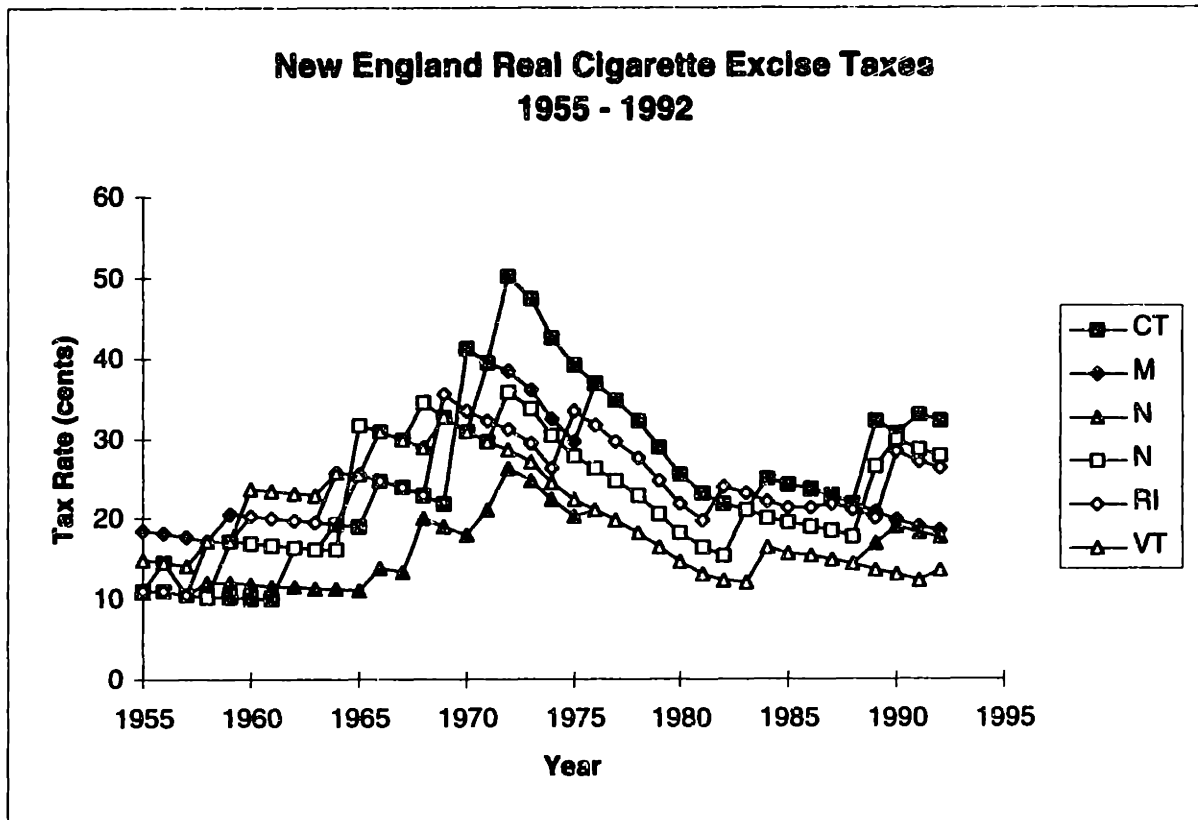


Figure 5-3: Real Cigarette Excise Taxes in New England, 1955 - 1992

ing aggregate demand equations from time-series data. Cigarettes, as addictive goods, are not generally considered to have close substitutes, which simplifies the public health analysis. As for the simultaneous determination of supply and demand, the existing literature analyzing times-series and panel data seems largely to have ignored the problem of simultaneity bias, proceeding on the unstated assumption that individual states act as small open economies in a world cigarette market where they face a perfectly elastic supply at a world price that they cannot affect (*see, e.g.*, Baltagi and Levin (1986); Baltagi and Levin (1992); Becker, Grossman, and Murphy (1990); Chaloupka and Saffer (1988)).

One standard technique for identifying systems of demand and supply equations and resolving the indeterminacy of simultaneity employs instrumental variables (Hausman 1983). At least one author, Chaloupka (1991), has estimated the demand for cigarettes using state excise taxes as instrumental variables to surmount the simultaneity problem, but most others (*e.g.*, Baltagi and Levin (1992); Keeler, Hu, Barnett, and Manning (1993)) combined federal and state excise taxes for their instrument.⁵ But, as discussed below, this study raises serious questions about the viability of excise taxes as instrumental variables, at least for the New England states.

In theory, state excise taxes should be nearly ideal instruments for the cigarette prices. Unfortunately, state excise taxes in New England do not provide a complete set of valid instruments. In both Massachusetts and Vermont, the variation in state excise taxes has been too small and too infrequent during the period studied for them to provide much help as instrumental variables.⁶

⁵One may question the advisability of including the federal excise taxes in the instrumental variable as they may be endogenous with the price. Harris (1987) argues that cigarette producers used the 1983 federal excise tax hike as a coordinating device for an oligopolistic price increase of twice the amount of the tax increase. Thus both theoretical and empirical considerations suggest certain concerns about the use of federal excise taxes as an instrument.

⁶This is particularly unfortunate as Massachusetts borders on all the other states in the study so that it is not possible to find a complete set of valid tax instruments for one of the other states either.

One may be tempted to estimate the demand equations without the prices from bordering states, ignoring potential cross-border effects, but this will not resolve the identification problem here precisely because one is trying to estimate the effects of out-of-state prices on in-state sales.

In a state without cross-border effects where cigarette excise taxes serve as a valid instrument, a Hausman (1978) test would serve to check to the specification. This would then suggest that prices in

There are good reasons to think that prices in the New England states considered are exogenous and that these states face an elastic supply of cigarettes at a given price. First, New England states comprise only a small proportion of cigarette demand in the United States. Collectively, the five New England states in the study accounted for only 7.5% of all state tax-paid cigarette sales in 1958, 9.3% in 1975, and 7.1% in 1992.⁷ Furthermore, the market for cigarettes is a world market. In addition, the wholesale cigarette distributors in New England operate not on a state but on a regional basis with territories spanning several states (Harris 1987). Since transportation costs are low in New England due to the small distances between states, one might reasonably assume that retailers face nearly the same wholesale cigarette prices.

Additional support for the assumption that the New England states all face the same producer price comes from examining the real price of cigarettes net of state excise taxes in each state. Figure 5-4 shows that these prices have been nearly equal over time among the states considered.⁸ On average, real cigarette prices among the states varied over the period considered by only $\pm 8.6\%$. When state sales taxes are included, prices among the states are equal within $\pm 3-4\%$. This study therefore assumes that, for the New England states, the supply of cigarettes is perfectly elastic at a given price. Given a world market for cigarettes, the proximity of these states, many of which are served by the same wholesaler, and their small share in national and international markets, this pivotal assumption does not appear unreasonable.

other states prices were exogenous. This approach was tried for California, estimating by maximum likelihood equation (1) with an AR(1) error process to correct for serial correlation. The Hausman test did not reject the hypothesis, $H_0: \beta_{OLS} - \beta_{IV} = 0$, with a χ^2 -statistic of 0.60 ($p = 0.74$).

⁷One state, Massachusetts, accounts for half those sales.

⁸The steady increase in the real cigarette prices over the last decade raises an interesting question: Is the observed decline in per capita consumption primarily due to an increase in the real price of cigarettes? Cf. footnote 13.

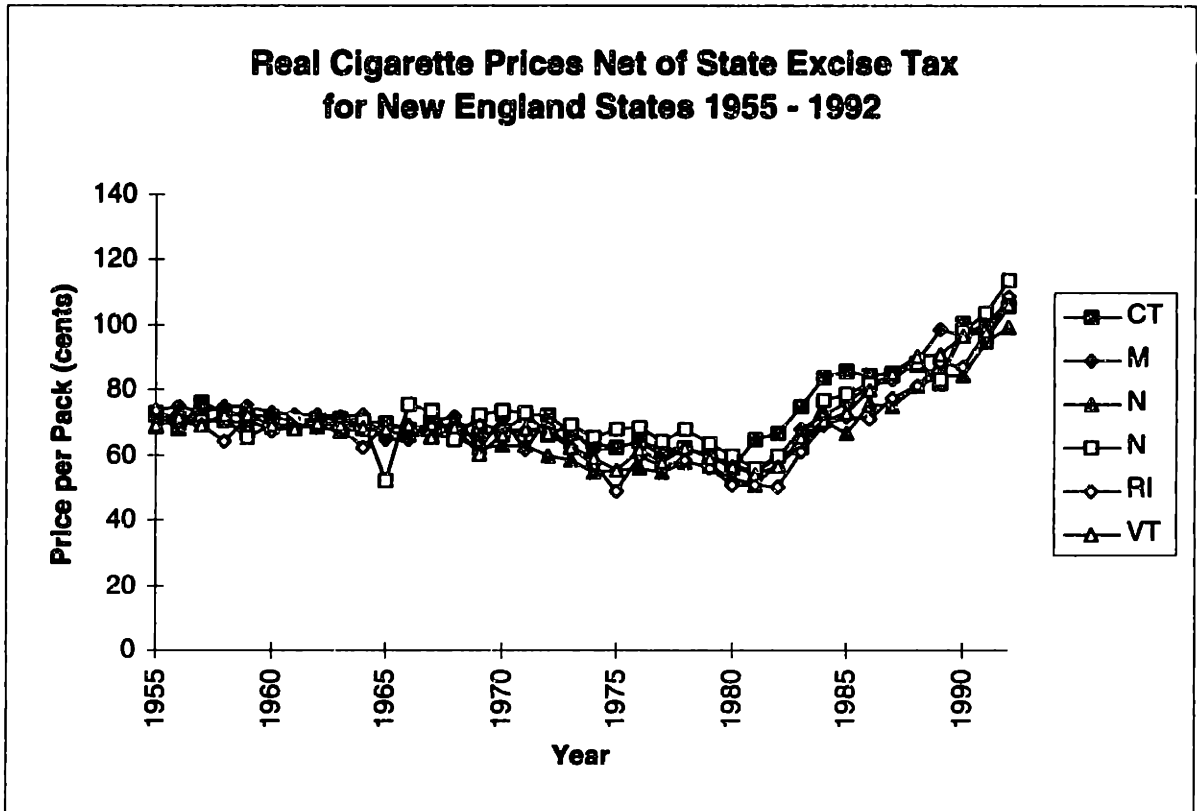


Figure 5-4: Real Cigarette Prices Net of State Excise Tax in New England, 1955 – 1992

5.2 Specification and Methodology

This study adopts a traditional model for cigarette demand. The model explains annual per capita cigarette sales in a given state i as a function of price, income, time, and prices in other states. The choice of variables is motivated by evidence from previous studies and considerations of economic theory. Data are aggregated over populations within each state and over the period of one year.⁹

Consider a linear regression specification for each state that relates the quantity of cigarettes purchased to the price at time t and other variables, such as per capita income, time, and prices in neighboring states, thought to affect sales. Expressing all variables, except time, in logarithms, the equation to be estimated takes the form

$$y_{it} = X_{it}\beta_i + u_{it} \quad (i = 1, \dots, M; t = 1, \dots, T) \quad (5.1)$$

where

y_{it} = state i 's annual per capita sales of cigarettes in year t ,

X_{it} = k_i x 1 vector of explanatory variables, including prices, income, a time trend, and a constant, affecting sales in state i in year t ,

β_i are the parameters (elasticities) to be estimated, for state i , and

u_{it} is an error term.

Parameters for each state may be estimated individually. Alternatively, the entire system of equations, rather than only a single equation, can be estimated by stacking the individual equations and treating equation 5.1 as a multivariate least squares regression.

Seemingly unrelated regressions estimation (SUR) is used to measure the elasticities of demand with respect to price, income, and prices in adjoining states. This methodology

⁹Cigarette demand is known to be a function of demographic variables, such as education, religion, and age. These are ignored in the present analysis, relying on the relative homogeneity of the New England states in contradistinction to an analysis that included, say, Utah, which has a significant Mormon population for whom smoking violates religious tenets.

is employed because the error term in the demand equation should be contemporaneously correlated with the error terms for the other New England states. The correlation arises from random shocks that a priori would be expected to affect all states similarly.¹⁰ Thus, efficiency is gained by employing the SUR variant of the generalized multivariate least squares model but not without cost. Misspecification of any equation in the system generally leads to inconsistent estimation in all equations in the system (Hausman 1983).

Many time series models exhibit serial correlation, and this can create problems for estimation. Omitted factors that are correlated over time cause the model to be misspecified, resulting in correlated residuals and inconsistent estimates. In a correctly specified model, although ordinary least square estimates remain unbiased, variance estimates are inconsistent and yield incorrect inferences. Finally, spurious regressions can arise when two independent variables are found to be correlated where in fact no relation exists, but both variables trend with time.

To provide for a more general autocorrelation scheme, one can relax the assumption that the u_{it} are serially uncorrelated. This allows for cases in which the effect of unobserved variables varies systematically over time, such as the effect of serially correlated omitted variables or the effect of transitory variables whose effects last for more than one period. Here a first-order autoregressive process for the error u_{it} is considered

$$u_{it} = \rho_i u_{it} + \epsilon_{it} \quad (5.2)$$

where ϵ_{it} are independently and identically distributed with mean zero and variance σ^2 .¹¹

Maximum likelihood estimates for an AR(1) error process were obtained on an equation-

¹⁰Consider, for example, the effect of the federal government attempts to reduce the consumption of cigarettes nationwide. Among them are: the release of the Surgeon General's Report in 1964, the requirement of warning labels on cigarette packing imposed by the Federal Trade Commission beginning in January 1965, the application of the Fairness Doctrine Act to cigarette advertising in June 1967, and the subsequent Congressional ban of all broadcast cigarette advertising in January 1971.

¹¹This analysis, of course, presumes that the series are stationary with well-behaved variance. Dickey-Fuller tests were performed for selected series to test for unit roots. Those tests did not reject the possibility of a unit root, which suggests looking at the sensitivity of the results to first differences.

by-equation basis, but maximum likelihood estimation of the entire system is complicated (Anderson and Hsiao 1982). Therefore an asymptotically efficient estimator of β using a multi-step procedure is computed instead.¹²

Since the misspecification of a single equation in the multivariate regression model affects estimates in all the equations, both equation-by-equation and system-wide regressions were computed and compared. As a check against spurious regressions, regressions in first differences were also calculated. The results of these and other regressions will be considered after first discussing the data.

5.3 Data

Estimation of the demand equation requires measurements for quantities, prices, excise taxes, and incomes. The data used in this study come from the Bureau of Economic Analysis, the Census Bureau, and The Tobacco Institute. Data for each of the New England states are available from 1958 through 1992, but the California data, used as a benchmark, only span 1960 through 1992. Since the states report based on a fiscal year, all data are measured on a June 30 basis. Price and income data have been converted to real amounts using the Bureau of Labor Statistics national consumer price index for urban areas, CPI-U [1982-1984 = 100].

¹²Following Greene (1993), the three-step approach of Parks (1967) was used. First, each equation was estimated by maximum likelihood for an AR(1) error process to obtain a consistent estimate of ρ . The individual equations were then transformed using the Prais-Winsten transformation, a generalized least squares transformation, to remove the autocorrelation. Second, ordinary least squares regressions were performed on each transformed equation, and a consistent estimate of Σ obtained from the residuals. Third, coefficient estimates were calculated by feasible generalized least squares (FGLS) on the transformed equations using the estimated Σ .

As Hsiao (1993) points out, the results are sensitive to the initial choice of ρ . This can be a problem for small samples such as the present since there are large number of consistent estimators for ρ , including those based on OLS, Prais-Winsten, Cochrane-Orcutt, Durbin and Hildreth-Lu procedures, all of which yield different estimates for ρ . The maximum likelihood estimate was chosen among the possible candidates as "the best one can do" given that one is willing to assume normal errors, but the use of other estimates did produce slightly different results. Since the estimator is efficient at every step and iteration does not result in a maximum likelihood estimator, there is no benefit to iteration although iterated FGLS did produce lower standard errors.

The sources and limitations of the data are discussed below for each variable.

Sales. Per capita cigarette sales are obtained from the total number of packs of cigarettes taxed in a particular state divided by the population for the state given by the July 1 Census Bureau estimates (Tobacco Institute 1993). Using per capita data adjusts for the effects of population growth on cigarette sales but mismeasures the cigarette consumption of smokers if the proportion of smokers in the population changes over time.

A potentially more serious measurement problem results from estimating the total number of packs sold by dividing the gross state excise tax revenues by the amount of the tax per pack. States typically offer discounts for quantity purchases of tax stamps but do not keep separate records for the quantity of discount sales.¹³ By ignoring these discount sales, the number of packs sold will be underestimated. In this study, it is assumed that discounts are not affected by changes in excise tax rates.

The special characteristics of cigarettes as a good mitigate two other potential problems in estimating the response of sales to a change in price or tax. Since cigarettes are perishable with only a few months shelf-life, inventory and hoarding problems should be small when aggregated over a year (Hu, Bai, Keeler, and Barnett (1991); Keeler, Hu, Barnett, and Manning (1993)). The addictive nature of smoking also means that cigarettes have few close substitutes, minimizing substitution effects in response to price changes (Harris 1987).

Income. Annual total personal income for each state was taken from the Survey of Current Business and converted to per capita amounts by dividing by the state population from the Census Population Reports.

Year. The year of the data was included as a regressor to estimate the trend of

¹³All New England states now offer some form of discount for tax stamps purchased in quantity and have in past years as well. For example, Vermont gave a 2.3% discount in 1993. Only recently have some states, like Rhode Island beginning in FY 1992, recorded the actual number of tax stamps sold. Estimates for total cigarette packs consumed during FY 1992 in Rhode Island differ slightly depending on whether gross excise taxes (104.5 million packs) or fusion stamp rolls sold (99.0 million packs) is used. The discrepancy may be due to revenue recognition in the accounting.

declining consumption over time shown in Figure 1 and the effects of anti-smoking regulations documented by other studies.¹⁴ (*e.g.*, Keeler, Hu, Barnett, and Manning (1993); Wasserman, Manning, Newhouse, and Winkler (1991)).

Prices. In November of each year, The Tobacco Institute surveys retail cigarette prices in each state to construct a weighted average retail price. The weights are based on the type of sale (*i.e.*, single package sold over-the-counter, carton, and vending machine) and assigned based on national market shares by type of sale. Beginning in 1991, the average retail price has included prices for generic brands, which now account for an estimated 20% to 30% of cigarettes sales and are cheaper than brand name cigarettes.

5.4 Empirical Results

Three separate types of regressions were run for each of the five New England states and California: ordinary least squares, AR(1), and first-difference. System (SUR) regressions were also computed for the New England states as a group. The equation-by-equation results have the advantage that the misspecification of one equation will not affect the estimation of the others as happens for the system regressions. The SUR results have an advantage in efficiency, however, if the errors among the states are contemporaneously correlated. Regressions were done both with and without prices for cigarettes in neighboring states.

The results of these regressions are presented by state in the Appendix. Columns 1 and 2, marked OLS, contain the ordinary least squares results; columns 3 and 4, labelled AR, the results of single equation maximum likelihood for AR(1); and columns 5 and 6, denoted FD, the OLS estimates of the first-difference equation. Similarly the results of the regressions for the entire system are given in the last three columns. Column 7, marked SUR, contains the estimates from the SUR model without correction for serial

¹⁴Using monthly data from California from 1980 to 1990, Keeler, Hu, Barnett, and Manning (1993) found that “[w]ithout the time trend, the effects of regulation are quite significant, but with the time trend included, regulation is not significant.”

correlation. Column 8, labelled SUR/AR, reports the results for the SUR model with an AR(1) error process where estimates for the individual state autocorrelation coefficients, ρ_i , were first estimated by maximum likelihood. Finally, the last column, SUR/FD, lists the results for the SUR model in first differences.

The estimated coefficients correspond to the variables listed at the left of the table with their standard errors given in parenthesis below them. Newey-West consistent standard errors were computed for the OLS and FD regressions. Summary statistics for the entire regression are reported in the last rows of each table.

An element of judgment necessarily tempers any assessment of the significance of these results. Durbin-Watson statistics reveal significant serial correlation in the errors of those regressions that do not account for autocorrelation. Because of the multicollinearity of the regressors and possibility for spurious regression results, blind reliance on t -statistics, even when the standard errors are consistent Newey-West estimates, as they are here, would be ill-advised.¹⁵ Instead, the dual criteria of statistical significance and economic plausibility were applied to the econometric results to assess the reliability of the elasticity estimates and the significance of cross-border effects. A significant negative coefficient on the price of a neighboring state, for example, calls into question the validity of the specification as it violates basic economic principles.

All the regressions concur that the coefficient on the state's own price is negative and that of other states' positive, when statistically significant, with only one exception.¹⁶ This accords with basic economic theory. One would expect the coefficient on the own price to be negative and that of the neighboring state prices to have a positive sign. That is, if the price in Massachusetts, which borders Rhode Island, rises, sales in Rhode Island also rise as Massachusetts residents buy cheaper cigarettes in Rhode Island.

¹⁵Newey-West estimates are known to be sensitive to the number of lags used, although that did not appear to be a problem here. Lags of length 1, 2 and 4 were tried. Newey-West estimates for two lags were used as they closely approximated those for four lags (within approximately 6%) but were generally larger. Lag length one was rejected to facilitate comparisons between the estimates which include a first difference.

¹⁶The ordinary least squares regression for California including the prices in border states gives a negative coefficient for Nevada.

Failure to account for cross-border effects biases the own price coefficients toward more positive numbers.¹⁷ Those states with significant cross-border effects, New Hampshire, Rhode Island, and Vermont, all show this effect as shown in a comparison of the results of regressions with and without adjoining state prices. This effect is not seen in Connecticut, where evidence of a significant cross-border effect from Rhode Island is more tenuous. Per capita sales responds differently to the other regressors depending on whether cross-border effects contribute to sales. This may account for some discrepancies previously mentioned among findings in the literature.

States with no cross-border effects, here California and Massachusetts, exhibit own price elasticities ranging from -0.54 to -0.22. These results are lower than those typically reported in the panel data literature but are consistent with the results from studies of micro-based data, which except for problems of under-reporting, are generally considered more reliable.

As expected, states with significant cross-border effects show a wide variation both in their own price elasticities, -2.89 to -0.15, and those with respect to border states, 0.32 to 2.84. Cross-border effects also strongly influence the estimates of income elasticities. Absent cross-border effects, states have income elasticities of 0.43 to 0.71 as compared to 0.0 to 0.88 for those exhibiting cross-border effects.

Single equation results generally accord well with system estimates. Estimation of an unrestricted SUR model provides for a test of the exclusion restrictions. Asymptotic χ^2 -squared tests of these restrictions strongly reject the joint hypothesis that all the

¹⁷Since one expects the coefficient on other states' prices to be positive, the direction of the bias if these prices are not included in the regression can be determined from the omitted variable formula. If the correctly specified regression model is

$$y = X_1\beta_1 + X_2\beta_2 + \varepsilon$$

but y is regressed only on X_1 , the expectation of β_1 will be biased

$$E[\beta_1] = \beta_1 + (X_1'X_1)^{-1} X_1'X_2\beta_2.$$

Selected State Resident Populations 1990 (in thousands)			
California	29,760	New Hampshire	1,228
Connecticut	3,287	New York	17,990
Massachusetts	6,016	Vermont	563
Maine	1,235	Rhode Island	1,003

Source: U. S. Bureau of Census, Current Population Reports.

Table 5.1: Selected State Resident Populations, 1990

coefficients of the excluded variables in the unrestricted SUR equation are zero.¹⁸ Since both the price and income series are highly correlated, however, this may not be so surprising.

In considering the role of potential cross-border effects, it is useful to keep in mind the relative populations, and their geographic distribution, of the New England states. Table 5.1 contains the populations of these states and California from the 1990 Census.

Comparison with a state unlikely to have significant cross-border effects also provides a useful test of the results. California, because of its size and the distance of its major population centers from the state borders, should not be significantly affected by cross-border transactions, as (Hu, Bai, Keeler, and Barnett 1991) have argued, and serves a benchmark for this study.¹⁹

Results for individual states are discussed below.

California. The OLS regression for California gives a negative coefficient for the Nevada price of -0.1965 (0.073), which has a *t*-statistic of 2.69. But the hypothesis

¹⁸The χ^2 -squared statistics with 34 degrees of freedom for the SUR regressions are 309.0 (no serial correlation correction), 81.5 (AR(1) error process), and 443.1 (first differences). These are highly significant as the critical value of $\chi^2(34)$ at the 0.005 significance level is 15.73.

¹⁹*But see*, Keeler, Hu, Barnett, and Manning (1993) who find a positive and significant coefficient on a weighted out-of-state price for California; *cf.* Hu, Bai, Keeler, and Barnett (1991) who conclude there is no cross-border effect for California with Keeler as a co-author.

New York state was rejected as a possible benchmark because New York city, containing a substantial proportion of the state's population, lies close by New Jersey and Connecticut and because New York shares a significant border with Canada, again with major cities on both sides of the border. Furthermore, a study by KPMG Peat Marwick and The Tax Foundation (1993) finds evidence for significant cross-border effects in New York City.

of a significant cross-border effect is rejected for three reasons. Ordinary least squares estimates give erroneous variance estimates in the presence of serial correlation. The errors reported are consistent Newey-West estimates, but the sample size is small. Nor do cross-border effects appear in either of the regressions that attempt to correct for serial correlation. Geographical considerations and the large proportion of California residents living far from the Nevada border also argue against any cross-border effect (Hu, Bai, Keeler, and Barnett 1991).

Connecticut. The own price elasticity estimates range from -0.60 to -0.45. The regression results suggest a possible cross-border effect from Rhode Island, but the evidence is not entirely compelling. Inclusion of prices from neighboring states, as noted previously, does not seem to increase the size of the own price elasticity as would be expected, although the differences are within the errors of estimation. In addition, Rhode Island historically has had lower cigarette prices than Connecticut. Any cross-border shopping then should arise from Connecticut residents purchasing cigarettes in Rhode Island. Rhode Island is the smallest New England state with easy access to Connecticut, but the region of Connecticut near Rhode Island is sparsely populated. Rhode Island's population is also only about one-third that of Connecticut. Consequently, if cross-border effects are important, one would expect to find a significant response in Rhode Island cigarette sales to the Connecticut price, but none was found. On balance, the evidence for a cross-border effect appears inconclusive.

Massachusetts. The results provide no evidence for a significant cross-border effect in Massachusetts from contiguous states.²⁰

New Hampshire. The findings for New Hampshire show that the price of cigarettes in Massachusetts is nearly as important to New Hampshire cigarette sales as New Hampshire's own price. Over the period studied, the New Hampshire price was consistently

²⁰New Hampshire shows a large response to the Massachusetts price but not conversely. This can be explained in terms of the relative populations of the two states. Massachusetts now holds roughly six times as many residents. Moreover, many southern New Hampshire residents commute to work in Massachusetts, but fewer go in the opposite direction.

lower²¹ than that in Massachusetts. Thus cross-border shopping by Massachusetts residents may explain part of the unusually high, at times double, per capita sales of cigarettes reported in New Hampshire. Although these findings are persuasive, they are subject to potential omitted variable bias. Both New Hampshire and Vermont border on Canada, but this effect could not be estimated without comparable data on Canadian cigarette prices. Since the tastes of American and Canadian cigarettes differ strongly, American and Canadian cigarettes are imperfect substitutes, which reduces potential cross-border effects from Canada.

Rhode Island. Rhode Island provides the most persuasive evidence for a cross-border effect. Rhode Island is a small state with a population only one-sixth that of Massachusetts. With only two bordering states, Rhode Island also provides the simplest case for analysis. Several large Massachusetts cities are close to the Rhode Island border, but nearby Connecticut is sparsely populated. A priori one would expect Massachusetts to play a more significant role in any cross-border effects Rhode Island, and the data confirm this. The coefficient on the Massachusetts price is significant and consistent across the various specifications while that for Connecticut is not, indicating that Rhode Island cigarette sales respond to cross-border effects from Massachusetts. Finally, correcting for cross-border effects increases the magnitude of the own price effect.

Vermont. Like New Hampshire, the Vermont analysis suffers from lack of information about potentially important cross-border shopping from Canada. Nonetheless there is evidence of a Massachusetts cross-border effect.

5.5 Conclusions

This study reaches several conclusions about the price and income elasticities of demand for cigarettes and the importance of cross-border effects among the New England states. For those states without significant cross-border effects, the estimated price and income

²¹By 14.8 cents on average in constant dollars over the period studied.

elasticities are consistent with those found in the literature, but show a lower response to price and a greater sensitivity to income than panel data studies. These estimates are, however, closer to the results of micro-based studies. For those states with significant cross-border effects, the own price elasticities are greater than previously reported, and prices in adjacent states matter. The effect of changes in income on per capita cigarette consumption for these states is greatly diminished. Finally, there is evidence for a general decrease in per capita consumption with time for the period studied, although its causes cannot be attributed.

The findings have implications for state and federal revenue and public health policies, as cigarette excise taxes have been used as mechanism to reduce smoking. Public finance economics teaches that taxing inelastic goods lessens efficiency losses. This study shows that state cigarette excise taxes can be a useful source of state revenues, but that the presence of cross-border effects diminishes their effectiveness for generating state revenue in high tax states while increasing it in low tax states. Cross-border effects also reduce force of state excise taxes as a policy measure to reduce cigarette consumption within a state. Both these considerations lead to the conclusion that federal cigarette excise taxes will be both more efficient in generating revenue and more effective as an instrument of public health policy.

5.6 Appendix: Results

Independent Variables	California					
	OLS	OLS	AR	AR	FD	FD
Constant	50.2622 (3.0583)	47.6941 (3.3749)	52.4332 (6.3045)	49.2728 (4.3656)	-0.0259 (0.0064)	-0.0241 (0.0060)
Price	-0.5636 (0.0286)	-0.3243 (0.0776)	-0.3074 (0.0592)	-0.2583 (0.0777)	-0.2804 (0.0424)	-0.2190 (0.0524)
Income	0.7073 (0.1138)	0.6001 (0.0885)	0.5621 (0.2040)	0.6416 (0.1689)	0.4816 (0.2180)	0.4393 (0.2023)
Year	-0.0251 (0.0021)	-0.0232 (0.0022)	-0.0261 (0.0039)	-0.0243 (0.0030)		
Price AZ		-0.0480 (0.0824)		-0.1149 (0.0853)		-0.0952 (0.0646)
Price NV		-0.1965 (0.0730)		-0.1553 (0.0868)		-0.0915 (0.0613)
Price OR		-0.0403 (0.0710)		-0.0371 (0.0732)		0.0135 (0.0430)
Rho			0.8821 (0.1136)	0.5605 (0.2093)		
N	33	33	33	33	32	32
R Squared	0.977	0.985	0.987	0.989	0.482	0.538
Adj. R Squared	0.975	0.982	0.985	0.985	0.446	0.449
Durbin-Watson	1.106	1.155	2.144	1.839	2.202	2.104

Table 5.2: California Regression Results

Independent Variables	Connecticut								
	OLS	OLS	AR	AR	FD	FD	SUR	SUR/AR	SUR/FD
Constant	49.5472 (4.7307)	50.5523 (5.9158)	44.8435 (7.6027)	48.3446 (8.6980)	0.8619 (1.0074)	1.1764 (0.9181)	53.4587 (6.2438)	51.9017 (8.1836)	0.0251 (0.0066)
Price	-0.6024 (0.0782)	-0.5907 (0.1018)	-0.5098 (0.0790)	-0.4725 (0.1068)	-0.4773 (0.1182)	-0.4678 (0.1093)	-0.6008 (0.1026)	-0.4639 (0.0995)	-0.4464 (0.0883)
Income	0.7352 (0.1356)	0.7829 (0.1683)	0.5706 (0.2179)	0.6478 (0.2501)	0.4934 (0.1961)	0.5081 (0.2230)	0.8797 (0.1907)	0.7743 (0.2345)	0.6632 (0.2215)
Year	-0.0248 (0.0030)	-0.0255 (0.0037)	-0.0218 (0.0048)	-0.0240 (0.0055)	-0.0004 (0.0005)	-0.0006 (0.0005)	-0.0273 (0.0040)	-0.0263 (0.0051)	
Price CT									
Price MA		-0.2341 (0.1695)		-0.2221 (0.1600)		-0.1768 (0.1021)	-0.2385 (0.1811)	-0.3275 (0.1557)	-0.2277 (0.1342)
Price ME									
Price NH									
Price NY		-0.1313 (0.1256)		-0.0315 (0.0998)		-0.0047 (0.0634)	-0.1268 (0.1284)	0.0016 (0.0892)	-0.0372 (0.0820)
Price RI		0.3238 (0.1483)		0.2127 (0.1114)		0.2441 (0.0667)	0.3088 (0.1347)	0.2392 (0.1044)	0.2521 (0.0938)
Price VT									
ρ			0.7296 (0.1507)	0.7500 (0.1560)				0.7500 (0.1560)	
N	35	35	35	35	34	34	35	35	34
R²	0.949	0.957	0.975	0.978	0.581	0.652	0.956	0.995	0.634
Adj. R²	0.944	0.947	0.971	0.972	0.632	0.575	0.947	0.994	0.569
D-W	0.617	0.700	1.973	1.701	2.284	1.991	0.719	1.681	1.885

Table 5.3: Connecticut Regression Results

Independent Variables	Massachusetts								
	OLS	OLS	AR	AR	FD	FD	SUR	SUR/AR	SUR/FD
Constant	42.1430 (5.2892)	33.8298 (4.3992)	40.0440 (6.1775)	37.8446 (7.5011)	1.2979 (0.7411)	1.0261 (0.8809)	40.6543 (4.5322)	37.2776 (7.3695)	-0.0175 (0.0049)
Price	-0.5891 (0.0765)	-0.5366 (0.0886)	-0.5251 (0.0766)	-0.3666 (0.1373)	-0.4382 (0.0552)	-0.3463 (0.0774)	-0.5357 (0.1497)	-0.3784 (0.1432)	-0.3531 (0.1071)
Income	0.6671 (0.1678)	0.5330 (0.1040)	0.6160 (0.1687)	0.5800 (0.1870)	0.4342 (0.1648)	0.4482 (0.1394)	0.7092 (0.1212)	0.5813 (0.1869)	0.5641 (0.1614)
Year	-0.0207 (0.0034)	-0.0159 (0.0027)	-0.0196 (0.0038)	-0.0182 (0.0046)	-0.0007 (0.0004)	-0.0005 (0.0004)	-0.0201 (0.0028)	-0.0179 (0.0045)	
Price CT		0.0173 (0.0688)		-0.0209 (0.0778)		-0.0271 (0.409)	-0.0378 (0.0697)	-0.0182 (0.0719)	-0.0200 (0.0640)
Price MA									
Price ME									
Price NH		-0.2476 (0.1563)		-0.1189 (0.1162)		-0.0701 (0.0847)	-0.1159 (0.1100)	0.0006 (0.1134)	-0.1066 (0.0828)
Price NY		-0.1221 (0.0811)		0.0174 (0.0829)		0.0166 (0.0724)	-0.1155 (0.0771)	-0.0004 (0.0699)	0.0392 (0.0634)
Price RI		-0.1061 (0.0903)		-0.0555 (0.0832)		-0.0482 (0.0497)	-0.0640 (0.0995)	0.0248 (0.0757)	-0.0549 (0.0684)
Price VT		0.4195 (0.1360)		-0.0137 (0.1430)		-0.0154 (0.1032)	0.2516 (0.0898)	-0.1449 (0.1327)	-0.0544 (0.1046)
ρ			0.8029 (0.1299)	0.8205 (0.1373)				0.8205 (0.1373)	
N	35	35	35	35	34	34	35	35	34
R²	0.920	0.938	0.966	0.969	0.600	0.617	0.934	0.997	0.594
Adj. R²	0.912	0.920	0.961	0.958	0.560	0.495	0.914	0.996	0.485
D-W	0.475	0.824	1.543	1.384	1.608	1.467	0.664	1.313	1.344

Table 5.4: Massachusetts Regression Results

Independent Variables	New Hampshire								
	OLS	OLS	AR	AR	FD	FD	SUR	SUR/AR	SUR/FD
Constant	97.4899 (25.2586)	25.8407 (28.0218)	46.7906 (24.0653)	26.3350 (25.2482)	7.1738 (1.6619)	7.4690 (1.6509)	31.9103 (28.2068)	22.4021 (28.3855)	-0.0119 (0.0140)
Price	-1.4051 (0.2022)	-2.9968 (0.6954)	-0.3618 (0.2322)	-0.8559 (0.3285)	-0.0269 (0.1671)	-0.6317 (0.3016)	-2.8883 (0.5943)	-0.1538 (0.3679)	-0.8659 (0.2722)
Income	2.1345 (0.7052)	0.4522 (0.5993)	0.8560 (0.4636)	0.3050 (0.4941)	0.4789 (0.3535)	-0.0728 (0.2969)	0.5992 (0.6199)	0.0664 (0.5337)	0.2649 (0.4215)
Year	-0.0535 (0.0159)	-0.0118 (0.0165)	-0.0242 (0.0138)	-0.0121 (0.0145)	-0.0036 (0.0009)	-0.0038 (0.0008)	-0.0155 (0.0168)	-0.0092 (0.0161)	
Price CT									
Price MA		2.9358 (0.5599)		1.0063 (0.3787)		0.8690 (0.2222)	2.8351 (0.6280)	1.3773 (0.4321)	0.9229 (0.3206)
Price ME		-0.9031 (0.7936)		-0.1089 (0.4040)		0.1114 (0.2454)	-0.9199 (0.7145)	-0.3530 (0.3695)	0.0995 (0.3324)
Price NH									
Price NY									
Price RI									
Price VT		0.5725 (0.7746)		-0.0562 (0.3980)		0.0056 (0.2793)	0.5447 (0.5848)	-0.7956 (0.4279)	-0.1245 (0.3303)
ρ			0.9449 (0.0732)	0.9557 (0.0794)				0.9557 (0.0794)	
N	35	35	35	35	34	34	35	35	34
R²	0.664	0.809	0.907	0.930	0.347	0.574	0.809	0.922	0.330
Adj. R²	0.632	0.768	0.894	0.912	0.282	0.479	0.768	0.905	0.210
D-W	0.514	1.282	1.517	1.522	1.844	1.797	1.226	1.549	0.210

Table 5.5: New Hampshire Regression Results

Independent Variables	Rhode Island								
	OLS	OLS	AR	AR	FD	FD	SUR	SUR/AR	SUR/FD
Constant	22.7891 (5.1856)	19.9094 (4.3693)	25.3129 (7.2954)	20.0887 (6.6497)	-0.8817 (1.5385)	1.2984 (1.2888)	20.2716 (3.9911)	22.0543 (5.7180)	0.0020 (0.0104)
Price	-0.7158 (0.0768)	-1.0994 (0.1186)	-0.7129 (0.0878)	-1.0598 (0.1379)	-0.7597 (0.1982)	-0.9703 (0.1063)	-1.1562 (0.1122)	-1.0909 (0.1186)	-1.0187 (0.1369)
Income	0.3812 (0.1622)	0.3003 (0.1630)	0.4721 (0.2384)	0.3232 (0.2182)	1.0160 (0.5407)	-0.0177 (0.5438)	0.3442 (0.1338)	0.3816 (0.1855)	0.0512 (0.3818)
Year	-0.0092 (0.0034)	-0.0078 (0.0028)	-0.0109 (0.0047)	-0.0080 (0.0043)	0.0004 (0.0008)	-0.0007 (0.0006)	-0.0081 (0.0026)	-0.0094 (0.0037)	
Price CT		-0.1206 (0.0821)		-0.1366 (0.1295)		-0.1607 (0.1542)	-0.2069 (0.0900)	-0.1269 (0.1051)	-0.1505 (0.1262)
Price MA		0.6729 (0.1667)		0.6775 (0.2062)		0.8499 (0.2182)	0.8073 (0.1666)	0.7278 (0.1765)	0.8358 (0.2069)
Price ME									
Price NH									
Price NY									
Price RI									
Price VT									
ρ			0.3865 (0.1693)	0.3931 (0.2015)				0.3931 (0.2015)	
N	35	35	35	35	34	34	35	35	34
R²	0.836	0.884	0.861	0.900	0.425	0.602	0.881	0.984	0.593
Adj. R²	0.821	0.864	0.842	0.879	0.368	0.530	0.860	0.982	0.537
D-W	1.237	1.227	1.833	1.770	2.322	2.322	1.210	1.738	2.265

Table 5.6: Rhode Island Regression Results

Independent Variables	Vermont								
	OLS	OLS	AR	AR	FD	FD	SUR	SUR/AR	SUR/FD
Constant	-23.3333 (1.0820)	-18.1923 (1.3153)	-25.2318 (3.3657)	-17.8150 (2.0464)	0.9657 (1.3643)	0.6393 (1.3454)	-17.9745 (1.9408)	-17.7002 (1.7940)	0.0150 (0.0080)
Price	-0.7966 (0.0950)	-1.3038 (0.1435)	-0.6169 (0.1149)	-1.3416 (0.1770)	-0.3299 (0.1589)	-0.6000 (0.4171)	-1.3434 (0.1589)	-1.5132 (0.1467)	-0.6148 (0.2758)
Income	-0.0034 (0.0034)	-0.0046 (0.0046)	0.0028 (0.0070)	-0.0072 (0.0063)	0.0022 (0.0019)	0.0026 (0.0038)	0.0007 (0.0052)	0.0032 (0.0050)	0.0065 (0.0068)
Year	0.0158 (0.0006)	0.0126 (0.0007)	0.0163 (0.0017)	0.0124 (0.0011)	-0.0005 (0.0007)	-0.0003 (0.0007)	0.0124 (0.0010)	0.0121 (0.0010)	
Price CT									
Price MA		0.7562 (0.2967)		0.8979 (0.2419)		0.3198 (0.3638)	0.6600 (0.2009)	0.9002 (0.2134)	0.3264 (0.2273)
Price ME									
Price NH		-0.1677 (0.2714)		-0.2012 (0.2415)		-0.1363 (0.2690)	-0.0351 (0.2065)	0.0690 (0.2199)	-0.1511 (0.2352)
Price NY		0.1542 (0.0830)		0.0901 (0.1298)		0.1426 (0.1235)	0.1796 (0.1109)	0.0740 (0.1100)	0.1551 (0.1554)
Price RI									
Price VT									
ρ			0.5708 (0.1931)	-0.2574 (0.1979)				-0.2574 (0.1979)	
N	35	35	35	35	34	34	35	35	34
R²	0.934	0.965	0.948	0.967	0.149	0.210	0.964	0.988	0.201
Adj. R²	0.928	0.958	0.941	0.958	0.064	0.034	0.957	0.985	0.058
D-W	1.173	2.206	2.101	1.853	2.290	2.397	2.045	1.603	2.314

Table 5.7: Vermont Regression Results

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years. Then in response to the need to raise revenues to cope with a widening federal deficit, Congress doubled the tax to 16 cents a pack, effected March 1, 1983, as part of the Tax Equity and Fiscal Responsibility Act of 1982. Although originally intended as a temporary measure that would be repealed on October 5, 1985, the new tax, after several extensions, became permanent in 1986.

States also typically raise cigarette excise taxes for fiscal rather than public health reasons, although anticipated public health benefits are often cited as justification. Cigarette excise taxes vary widely among states and across time.

Age distribution. Census estimates based on projections, verifications, and sampling corrections provide the population by age cohort nationally and for each state. National population statistics from 1950 are given in the finest published detail.

Income. Annual average total personal income for each state was taken from the *Survey of Current Business* (Bureau of Economic Analysis, U.S. Department of Commerce various years) and converted to per capita amounts by dividing by the state population from the *Census Population Reports*. For the national time series data set, per capita disposable income is used as the income variable.

Advertising and promotional expenditures. The U.S. cigarette advertising and promotional expenditures for 1975 to 1993 are reported in the annual Federal Trade Commission Reports to Congress and compiled in the USDA's *U.S. Tobacco Statistics* (Creek, Capehart, and Grise 1994). Advertising and promotional expenditures rose from 10% of the wholesale price of cigarettes in 1975 to 18% in 1993.

During this time period, the composition of cigarette advertising and promotional expenditures underwent a dramatic change as cigarette manufacturers switched from advertising to direct-to-consumer marketing as their principal form of promotion. In 1975, advertising in newspapers in magazines dominated cigarette advertising and promotional expenses, comprising 57.9% of all such expenditures. By 1993, advertising had plummeted to 4.5% of total expenditures. At the same time, promotional allowances and other expenses, which include direct mail, endorsements, and coupons, soared from