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Public Policy and Market Competition: How the Master Settlement Agreement Changed the Cigarette Industry*

Federico Ciliberto and Nicolai V. Kuminoff

Abstract

This paper investigates the large and unexpected increase in cigarette prices that followed the 1997 Master Settlement Agreement (MSA). We integrate key features of rational addiction theory into a discrete-choice model of the demand for a differentiated product. We find that following the MSA firms set prices on a more elastic region of their demand curves. Using these estimates, we predict prices that would be charged under a variety of industry structures and pricing rules. Under the assumptions of firms' perfect foresight and constant marginal costs, we fail to reject the hypothesis that firms collude on a dynamic pricing strategy.

KEYWORDS: cigarettes, Master Settlement Agreement, discrete choice, demand, competition

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1. Introduction

This study investigates the Master Settlement Agreement's impact on the nature of competition in the cigarette industry. In 1997, the major cigarette companies signed the Master Settlement Agreement (MSA) with the attorneys general of all 50 states. This agreement released the industry from lawsuits brought against them by the states in exchange for billions of dollars of annual payments to be made in perpetuity. The structure of these payments effectively raised the federal per-pack tax on cigarettes by 44 cents. However, in the first few years following the agreement, cigarette firms raised prices by *more than one dollar*. This ended a wild decade for cigarette pricing.

FIGURE 1: Average Price of a Pack of Premium Cigarettes. (Net of State, Federal, and MSA Taxes)

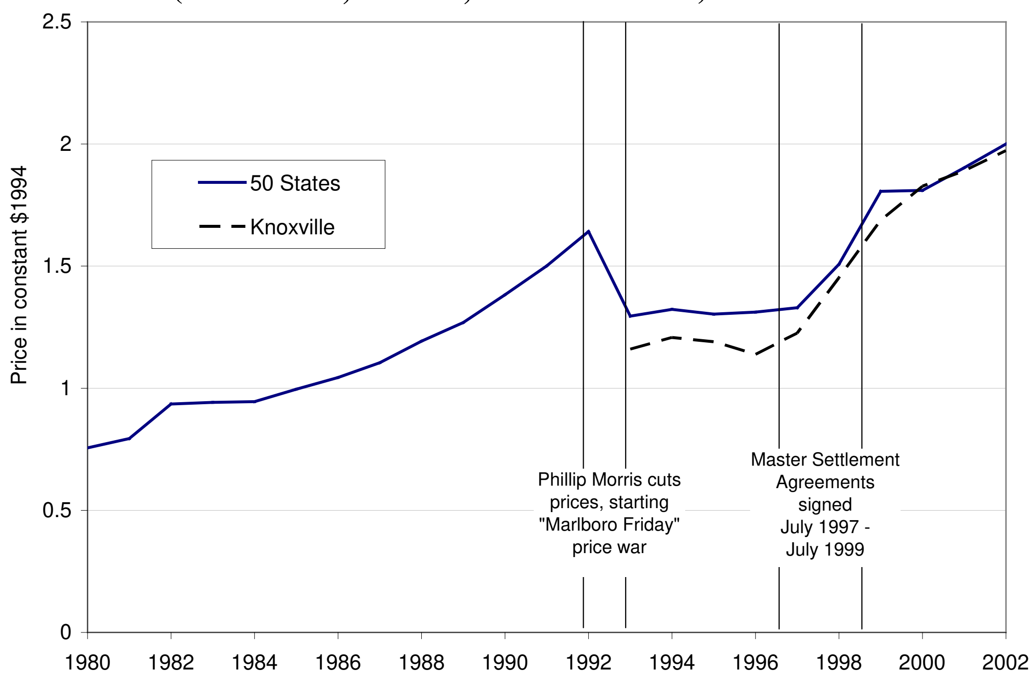


Figure 1 illustrates the dramatic swings in cigarette pricing that occurred during the 1990s.[1] Between 1980 and 1992, the average price of cigarettes increased at a constant rate. Then, on April 3, 1993, Philip Morris dropped the price of Marlboro cigarettes by 40 cents, starting the famous "Marlboro Friday" price war (Issacson and Silk, 1997). After Marlboro Friday, cigarette prices

[1] As we will discuss later, Figure 1 compares the time trend in the Knoxville data with the average state price of premium cigarette packs net of federal and state taxes, and net of the per/unit effective tax imposed by the MSA (from Table 1). The two trends are very similar.

remained flat until the MSA was signed in 1997, at which point prices approximately returned to their pre-war rate of growth. Our main objective in this article is to infer the nature of competition in the cigarette industry and to investigate whether the MSA served as a coordinating device for firms to terminate their price war and collectively raise prices.

Our analysis begins by developing a differentiated product model of the demand for cigarettes. We integrate key features of Becker and Murphy's (1988) rational addiction logic into the discrete-choice model of the demand for differentiated products developed by Bresnahan (1987), Berry (1994) and Berry et al. (1995), henceforth BLP. The resulting model depicts smokers who get utility from pack characteristics, and whose current consumption decisions depend on their past consumption and on their expectations for the evolution of future prices.

The econometric model is estimated using quarterly scanner data on the sales of 291 different cigarette packs and cartons sold at five supermarkets in Knoxville, Tennessee between 1993 and 2002. For each product, our data contain a comprehensive set of characteristics including price, length, advertised strength, packaging, and menthol content. A key challenge during the estimation is to address the potential endogeneity of current and future prices that may stem from their dependence on unobserved pack characteristics. We address this challenge by constructing two separate sets of instruments. Instruments for current price are constructed from measures of the tar and nicotine content of each pack. Instruments for future prices are constructed in a way that exploits the quasi-experimental nature of the MSA. More precisely, we construct dummy variables for the pre-MSA and post-MSA periods that capture the way in which the MSA changed smokers' expectations on future cigarette prices.

Our econometric results are consistent with the idea that consumers are forward-looking and that their current smoking decisions are affected by their past consumption. The corresponding price elasticities imply that firms set prices on the inelastic region of their pack-level demand curves prior to the MSA. The possibility that firms set prices near marginal cost during this period is consistent with the "Marlboro Friday" price war. Following the MSA, we see firms setting prices on the elastic region of their demand curves. This provides preliminary evidence that the MSA changed the nature of competition in the industry. The ability to infer pricing behavior from data in a single metropolitan area stems from the fact that spatial variation in cigarette taxes creates an incentive for firms to set prices locally (Sumner 1981; Sullivan 1985; Ashenfelter and Sullivan 1987).

To further investigate the competitive structure of the industry, we combine our demand estimates with pack-level estimates for marginal cost to ask the following question: *which models of equilibrium conduct are capable of explaining firms' actual pricing behavior?* We compare actual prices with the prices that would be charged by a Bertrand-Nash oligopoly and by a collusive industry. Within each of these two frameworks we consider three pricing rules: (1) static price setting; (2) “boundedly rational” price setting where firms only consider the current period and the following period; and (3) “dynamic” price setting, where firms consider the entire stream of future prices when they set current prices. In the “boundedly rational” and “dynamic” models, we assume that firms set current prices given perfect foresight on future equilibrium prices. The advantage of imposing perfect foresight is that it allows us to relax the assumption that firms play Markov-perfect strategies, as is usually maintained in empirical studies of dynamic behavior.

For each of the six models of pricing behavior, we compare actual cigarette prices with 95% confidence intervals on predicted prices. Prior to the MSA, actual prices are far below the lower bound on the predictions from all six models. Following the MSA, actual prices are consistent with dynamic pricing strategies. If firms set price near marginal cost during the Marlboro Friday price war, then only one model of firm behavior is consistent with observed pricing behavior after the MSA: *a collusive industry with dynamic price setting*.

Our paper makes a number of contributions. First, to the best of our knowledge, it is the first study that estimates a differentiated product model of the demand for cigarettes. Second, it introduces habit formation (addiction) into a standard BLP-style model, treating the stock of previous purchases as a latent variable. Third, the analysis is based on a new dataset. Fourth, our paper proposes a unique set of instruments for cigarette prices that are based on product characteristics that are difficult for consumers to observe, but have an impact on production costs. Finally, and most importantly, we document that the MSA had a significant impact on cigarette pricing. In particular we provide evidence that is consistent with a dramatic shift from a pre-MSA price war to post-MSA collusion.

Section 2 begins our analysis by providing background on the cigarette industry and illustrating how the Master Settlement Agreement effectively raised the federal tax on cigarettes. This tax was dwarfed by the increase in prices that followed the MSA. To provide context for our subsequent analysis of this price increase, Section 3 briefly reviews the existing literature on addiction, taxation, and market power in the cigarette industry. Then, Section 4 develops our microeconometric model of smoking behavior. It begins from a simple model of utility-maximizing behavior for a forward-looking smoker who is addicted to cigarettes. After discussing how we model expectations and addiction, Section 5 presents the econometric model and discusses identification. Section 6 describes the data used during the estimation. We discuss the resulting demand estimates in Section 7, conduct the revealed-preference analysis of the supply side of the market in Section 8, and provide concluding comments in Section 9. Additional details on the MSA and robustness checks on the estimation are provided in a supplemental (online) Appendix.

2. The Cigarette Industry and the Master Settlement Agreement[2]

Throughout the past century, six firms accounted for virtually all cigarettes produced in the United States. In 1997, five of these firms accounted for 99.9% of domestic sales: Philip Morris (49.2%), RJ Reynolds (24.5%), Brown and Williamson (16.2%), Lorillard (8.7%), and Liggett (1.3%) (Bulow and Klemperer 1998).[3] Each of these companies produces multiple brands (such as Camel, Marlboro and Salem) and each brand is associated with multiple packs that differ in their length, strength, flavor, and packaging.

The multiplicity of cigarette brands can be divided into two broad categories, *discount* and *premium*. For much of the 20th century, virtually all cigarettes were considered premium. This changed in 1980, when Liggett introduced discount cigarettes which cost a few cents less per pack to produce but had much smaller advertising budgets and were sold at a substantial discount. The other firms soon followed by introducing their own discount brands. Throughout the 1980's and early 1990's, the market share of discount brands increased, peaking at 40% of total cigarette sales in 1997 (Federal Trade Commission, 1997). As a result, the premium brands suffered substantial declines in market share. Marlboro experienced some of the largest losses. Its sales decreased by 5.6% during 1992 and then declined by another 8% during the first three quarters of 1993.

In response to declining sales, Philip Morris dropped the price of Marlboro cigarettes, its leading brand, by 40 cents on Friday April 3, 1993. After Philip Morris dropped the price of Marlboros, the other cigarette manufacturers lowered their prices as well, initiating a price war that would last for the next four years. Figure 1 illustrates that the real national average retail price of cigarettes fell from \$1.64 in 1992 to \$1.29 in 1993. April 3, 1993 has since become known as "Marlboro Friday" in the industry. Marlboro Friday and the subsequent price war have been widely studied in the business literature (e.g., Issacson and Silk, 1997). After Marlboro Friday, prices remained relatively flat until the Master Settlement Agreement was signed in 1997.

To understand the implications of the Master Settlement Agreement, it helps to have some background on cigarette taxes. Cigarettes are taxed at the local, state, and federal levels. In 2000, the federal tax increased from 24 cents

[2] The supplemental appendix presents more detailed discussion of the institutional features of the cigarette industry.

[3] The sixth major company, the American Tobacco Company, was purchased by Brown and Williamson in 1995. In 1999, Philip Morris purchased the *L&M*, *Chesterfield*, and *Lark* brands from Liggett, and in 2004, R.J. Reynolds and Brown & Williamson merged.

per pack to 34 cents, which was followed by an increase to 39 cents in 2002. The variation in taxes across states is considerably larger. During 2005, the state tax on a single pack of cigarettes ranged from \$0.025 in Virginia to \$2.05 in New Jersey. As of 2009, more than 450 local jurisdictions had additional taxes as high as \$2.00 per pack in Cook County, Illinois.[4] Variation in state and local taxes, combined with restrictions on inter-state trading, creates an opportunity for firms to engage in spatial price discrimination. This observation has provided the basis for previous studies of market power in the industry (Sumner 1981; Sullivan 1985; Ashenfelter and Sullivan 1987).

Traditionally, each of the top five firms has provided one official wholesale price for each brand of cigarettes it sells in the U.S. However, as Sumner (1981) first observed, this national "list" price is not the price at which cigarettes are actually sold. The actual market price includes discounts, coupons, and other promotions that can vary across states and localities. This has become an increasingly important factor in pricing strategy. According to the Federal Trade Commission (2007), expenditures on cigarette promotion during 2001 totaled \$4.5 billion, up from \$0.2 billion in 1981.

While promotional expenditures and spatial variation in cigarette taxes have both risen over time, smoking in the U.S. has declined steadily since its peak in 1963. Between 1971 and 2001, cigarette sales per capita decreased by more than half. The decrease in consumption reflects rising prices, health concerns and changing social attitudes toward smoking. As social attitudes have changed, so have attitudes toward the cigarette companies. Public perception of the industry became increasingly negative during the 1990's, largely due to the realization that the companies had withheld information about the health consequences of smoking. This new information made it easier to win lawsuits against the companies, and the number of court cases skyrocketed (Bulow and Klemperer, 1998).

In response to increasing legal expenses, Philip Morris, RJ Reynolds, Brown and Williamson, and Lorillard signed a series of agreements between July 1997 and July 1999, with tobacco growers and with the attorneys general from the 50 states. We refer to these agreements collectively as the Master Settlement Agreement, or MSA.[5] The MSA releases participating manufacturers from preexisting and future lawsuits brought against them by the states and tobacco growers. In exchange, the manufacturers agreed to pay, in perpetuity, billions of dollars in annual lump-sum payments. While most of these payments are transferred to the

[4] Data on local taxes are available from tobaccofreekids.org.
[5] By mid-2003, 40 more companies had signed the agreement, including Liggett. As an incentive to sign, the MSA contains provisions that require each state to extract special payments from manufacturers that have not signed.

states and to tobacco growers, a small share has been used to establish foundations to reduce youth smoking and to enforce other provisions of the MSA.[6]

TABLE 1: The Master Settlement Agreement (Payments in Millions of Dollars)[a]

	1	2	3	4	5	6	7	8
Year	States	Florida, Minnesota, Mississippi, Texas	National Public Education Fund	Attorney fees	Tobacco growers	Total Scheduled Payment	Actual Payment	Effective per pack tax (cents)
1997		1,827				1,827	1,827	0
1998	3,080	495	325	500		4,400	4,400	0
1999	7,737	253	325	500	380	9,195	7,600	33
2000	8,396	253	325	500	280	9,754	8,191	36
2001	10,228	253	325	500	400	11,705	9,535	44
2002	10,306	253	325	500	500	11,884	9,560	44

[a] In 1998, Column 3 includes $50 million used to establish the Consumer Protection Tobacco Enforcement Fund.

Table 1 summarizes the payments made by the cigarette manufacturers under the MSA. The first six columns reflect the baseline level of payments scheduled by the agreement. Scheduled payments to the states are listed in Column 1. Column 2 reports some additional payments made to four states that signed special agreements with the manufacturers. Column 3 shows payments to the *National Public Education Fund*, which aims to reduce youth smoking, Column 4 shows fees paid to the attorneys, and Column 5 shows scheduled payments to tobacco growers. Finally, Column 6 reports the total scheduled payments.

Actual MSA payments (Column 7) have been substantially lower than their scheduled levels due to an automatic adjustment that decreases the payments in Columns 1 and 5, if the volume of industry sales decreases relative to 1997.[7] Equation (1) illustrates how this *volume adjustment* transforms the annual MSA payment from a lump sum into an effective per/pack tax.

$$\overline{MSA_t} = MSA_t - MSA_t(a_t)(0.98)(1 - Q_t / Q_{1997}). \tag{1}$$

[6] For example, the MSA requires the industry to restrict certain types of marketing and advertising. See Cutler et al. (2002) for a detailed analysis of the agreement.

[7] The payments are also adjusted for inflation and loss of market share to non-participating manufacturers. However, the impact of these adjustments is small compared to the volume adjustment during our study period.

$\overline{MSA_t}$ denotes the actual lump-sum payment made by cigarette manufactures in year t. The size of this payment depends on the scheduled payment (MSA_t), the total number of packs sold in 1997 (Q_{1997}), the total number of packs sold in year t (Q_t), and the proportion of scheduled payments subject to the volume adjustment (a_t). This incentive structure is equivalent to a per-pack tax (see the supplemental Appendix for details). Column 8 reports the size of this tax. In 2002 for example, it was equal to 44 cents per pack.

Given the effective tax created by the volume adjustment, it should come as no surprise that, since the agreement was signed, cigarette manufacturers have increased their prices and sales have declined. What has been surprising is the magnitude of the price increases. Immediately after signing the MSA, the participating manufacturers raised the price of all packs by 45 cents. This was followed by numerous smaller increases over the next four years. By the end of 2002, the national average price of cigarettes had increased by more than a dollar since 1997, after netting out increases in state and federal taxes. A simple explanation for this surprisingly large price increase would be that wholesalers and retailers impose additional (percentage) markups. However, the existing literature on the price sensitivity to cigarette taxes concludes that wholesalers and retailers set markups at a fixed dollar amount above costs, rather than as a percentage (e.g., Sumner 1981; Cutler et al. 2002). Another explanation is that the process of negotiating the MSA provided an opportunity for the cigarette firms to agree to collectively raise prices. Before investigating this possibility, we first provide a brief review of the existing literature on addiction, taxation, and pricing strategy in the market for cigarettes.

3. A Brief Review of Cigarette Addiction and Market Competition

As a highly concentrated oligopoly that sells a controversial product, the cigarette industry has received considerable attention. The literature on the economics of smoking has addressed a wide range of issues including market power, taxation, advertising, youth smoking, smuggling, health, and addiction. In this section, we briefly summarize key results in three areas of the literature that are relevant for our analysis: market power, taxation, and addiction. Readers seeking a comprehensive review should begin with Chaloupka and Warner (2000).

Compared to other prominent oligopolies, the distinguishing feature of the cigarette industry is that it sells a chemically addictive product. Addiction can be characterized by a choice process that exhibits *reinforcement* and *tolerance* (Becker and Murphy, 1988). Smoking is reinforcing in the sense that past consumption increases the marginal utility from current consumption. As one smokes more today, his tolerance increases, meaning he will obtain less utility from the same level of consumption in the future. Becker and Murphy integrate these concepts into their theory of rational addiction which envisions forward-looking consumers making optimal choices based on a stable preference function and a constant discount rate.

The initial tests of rational addiction were conditioned on the maintained assumption that, regarding prices, consumers have perfect foresight into the distant future (Chaloupka 1991; Becker et al. 1994). There are two difficulties with this assumption. First, changes in excise taxes are rarely announced more than three months in advance. Second, this assumption ignores adjustment on the part of firms.[8] While consumers' foresight may be less than perfect, Gruber and Köszegi (2001) provide strong evidence that consumers are forward-looking. Using monthly data between the enactment of a new tax and the date it went into effect, they find that the decrease in consumption that precedes an impending tax increase is equivalent to the consumption response to past and current taxes. Arcidiacono et al. (2007) and Coppejans et al. (2007) provide additional evidence in support of forward-looking behavior.

In contrast to the rational addiction literature, past studies that have attempted to infer the degree of market power in the industry have adopted a myopic framework. Sumner (1981) developed the first econometric test of market power in the industry. He observed that variation in excise taxes across states and time creates an incentive for firms with market power to price discriminate. Under the maintained assumption that the market-level demand elasticity is constant, a price discriminating firm will raise price by more than the amount of a new excise tax. Sumner estimates the reduced-form relationship between cigarette prices and excise taxes, finding evidence of price discrimination but of a magnitude that is sufficiently small to reject the hypothesis of cartel behavior. This result is reinforced in subsequent studies by Sullivan (1985), Ashenfelter and Sullivan (1987), and Raper et al. (2007).

An alternative explanation for the empirical relationship between cigarette prices and taxes stems from Barzel (1976). He hypothesizes that as the per-unit tax on a set of heterogeneous goods increases, consumers will reduce their consumption and substitute toward untaxed quality attributes, which, in turn, will increase average product quality and average market price. The introduction of discount cigarettes in the 1980's, provided a convenient way to test this form of compensating behavior. Sobel and Garrett (1997) apply Barzel's theory to cigarettes using data on discount and premium market shares together with prices and tax rates. They find that a 3-cent increase in sales tax increases the market share of premium cigarettes by 1 percent, providing evidence in support of Barzel's theory. In related work, Evans and Farrelly (1998), Farrelly et al. (2004), and

[8] Forward-looking oligopolists who recognize their product is addictive would maximize profits by raising prices in response to decreases in lagged consumption (Showalter, 1999).

Adda and Cornaglia (2006) present evidence that smokers compensate for tax increases by switching to cigarettes with higher concentrations of tar and nicotine, and by adapting their smoking style to extract more nicotine from each cigarette.

4. The Model of Demand

A unifying feature of the rational addiction and market power studies cited in the previous section is that they treat cigarettes as a homogeneous product, measuring quantities in terms of aggregate sales or aggregate consumption. Homogeneity has become an increasingly unrealistic characterization over the past two decades as firms have segmented the market by introducing discount brands while simultaneously increasing their annual advertising expenditures by more than 500% in real terms (Federal Trade Commission, 2007).[9] Because the major cigarette manufacturers each sell multiple brands which are differentiated by their advertised image, we would expect pricing behavior to be influenced by cross-price elasticities. Thus, we depart from the existing literature by treating cigarettes as a differentiated product.

4.1. Utility Function

Consider a market with $i = 1,..., I$ consumers, each of whom chooses among $j = 1,..., J$ packs in each of $t = 1,...,\infty$ time periods. We depict a consumer's choice between differentiated packs at a single point in time, recognizing that current consumption depends on past smoking behavior and on expectations for future prices. Equation (2) represents the utility associated with consumer *i*'s choice to purchase pack *j* at time *t*:

$$u_{ijt} = x_j \beta_i + \alpha_i p_{jt} + \varphi A_{it} + \gamma p^e_{jt+1} + \xi_{jt} + \varepsilon_{ijt} . \qquad (2)$$

In the equation, x_j is a *k*-dimensional vector of pack characteristics observable to both consumers and the econometrician, and β_i is a vector of taste parameters. Observable pack characteristics are assumed to remain constant across time, stores and consumers.[10]

We follow the rational addiction literature by assuming consumers' preferences are constant over time and that smokers recognize the dependence of cur-

[9] See Porter (1986) for an empirical study on the effects of advertising on cigarette consumption.
[10] The influence of price on a consumer's choice is represented by $\alpha_i p_{jt}$ where $-\alpha_i$ is the consumer's marginal utility from income. This term is also consistent with models of vertical product differentiation, where $-1/\alpha_i$ would be interpreted as the value that a consumer puts on tobacco quality. A larger value for α_i implies a lower desire for quality.

rent consumption on past consumption decisions. That is, an individual's utility from smoking in equation (2) depends on the extent to which they are addicted to cigarettes. This is reflected in the φA_{it} term, where $\varphi > 0$, and A_{it} represents an individual's stock of addiction. Rational addiction theory also suggests that smokers will be forward-looking with respect to price (Gruber and Köszegi, 2001).[11] An increase in the expected price of pack *j* in the next period (p^e_{jt+1}) will decrease the utility from consumption today ($\gamma < 0$) because addicted smokers recognize that increasing their stock of addiction by choosing to smoke today will increase their future expenditures on cigarettes. Since the rational addiction logic implies $\varphi > 0$ and $\gamma < 0$, econometric estimates for the signs of these parameters provide a test on the theoretical consistency of our model.

Consumers may differ in their tastes for cigarette characteristics and tobacco quality. To illustrate this, let θ_i represent a vector of all the structural parameters, $\theta_i = [\beta_i, \alpha_i, \varphi, \gamma]$. We assume that a representative consumer's preferences can be expressed as: $\theta_i = \psi + \Pi D_i + v_i$, where ψ is a vector of means, Π is a matrix of coefficients measuring how tastes vary with a vector of demographic characteristics (D_i) that describe consumer *i*, and v_i is a vector of idiosyncratic tastes that follow a known distribution.

The last two terms in Equation (2) represent mean utility from pack characteristics that are observed by consumers and firms, but not by the econometrician (ξ_{jt}), and consumers' idiosyncratic tastes for individual packs (ε_{ijt}). We close the model by assuming the existence of an outside good ($j = 0$) which represents the decision not to smoke cigarettes (i.e., quitting).

BLP demonstrate that the market share of the j^{th} pack can be expressed as a function of the mean utilities of all goods, given the structural parameters. Relative to their specification, the novelty of our model is that current-period utility depends on consumers' past smoking decisions (A_t) as well as their expectations for firms' future pricing decisions (p^e_{t+1}). Therefore, prior to estimation, we must first specify how the stock of addiction evolves over time and how consumers form expectations on future prices.

[11] Coppejans et al. (2007) provide evidence that current consumption choices made by addicted smokers who are forward-looking will depend on their expectations for the evolution of future prices. Their theoretical model uses the dynamic optimization problem faced by a forward-looking representative agent to demonstrate that an increase in future price variability will decrease future consumption of an addictive good. This result is supported by their evidence on the reduced-form relationship between current cigarette consumption and future price volatility.

4.1.1. Modeling Expectations on Future Prices

Gruber and Köszegi (2001) point out that it is problematic to expect consumers to predict future cigarette prices perfectly, partly because price increases are rarely announced more than a few months in advance. At the same time, Sloan et al. (2003) provide evidence that smokers are cognizant of long-term trends in cigarette pricing. Therefore, we adopt an intermediate approach between perfect foresight and myopic behavior that is consistent with both Gruber and Köszegi (2001) and Sloan et al. (2003). Rather than attempting to model consumers' expectations for the level of future prices, we use a dichotomous variable to indicate whether smokers expect prices to increase in the future.[12]

We set p^e_{jt+1} equal to 1, if the average real price of cigarettes in the previous quarter was higher than the average price one year earlier. Otherwise, p^e_{jt+1} is set to equal zero. The idea is that past price changes affect the way smokers form expectations on future prices. Clearly, this variable is meaningful for the empirical analysis only if there are both upward and downward price shocks in the data. Fortunately, this is the case (see Figure 1). Between Marlboro Friday and the signing of the MSA, prices were roughly constant or declining. Following the MSA, prices increased steadily.

4.1.2. Modeling Addiction

We depict the evolution of an individual's stock of addiction to cigarettes using the following law of motion:

$$A_{it} = a_{it-1}\left[1 + (1-\delta)A_{it-1}\right]. \tag{3}$$

A_{it} is their addiction stock at time *t*. It depends on the addiction stock in the previous period, A_{it-1}, the rate at which the stock depreciates, δ, and an indicator variable that equals 1, if the individual chose to smoke in the previous period, a_{it-1}. Notice that addiction is not pack specific. Smokers are assumed to become equally addicted, regardless of which pack they choose to smoke. This is consistent with the choice process implied by the utility function in (2). A larger stock of addiction increases the probability of choosing to smoke (given $\varphi > 0$) but has no influence over which pack is chosen. The intuition behind this feature of the

[12] In addition, it is difficult to interpret the coefficient on the expected price. The instrumented variable captures any change in demand that occurred post-MSA. While one component of the change may be due to changing price expectations, any factor which decreases the demand for smoking, such as changes to laws affecting smoking in public places, would also be captured by the coefficient.

model is that the physical symptoms of nicotine withdrawal do not depend on which pack(s) an individual is accustomed to smoking. If an individual decides to quit, their stock of addiction drops to zero in the following period (i.e. $A_{it} = a_{it-1} = 0$). A discrete drop in addiction could be explained by the use of a chemical aide designed to break the physical dependence on nicotine (e.g., inhalers, patches, pills, gum).[13] While quitting reduces the probability that the individual will choose to smoke in the following period, it does not preclude a relapse.

The time path for an individual's stock of addiction ($A_{i1},..., A_{iT}$) can be constructed from Equation (3) using three pieces of information about the individual: (i) their sequence of smoking decisions over the first T-1 periods, $a_{i1},...,a_{iT-1}$, (ii) their prior smoking habits, as reflected in their period 1 stock of addiction, A_{i1}, and (iii) the rate at which their stock depreciates. We assume the depreciation rate is known to the econometrician and focus on the first two components.[14] In principle, both could be collected from long panel surveys of individual smoking behavior and cigarette purchases. Unfortunately, such data are not readily available. Therefore, we propose a simple approach that uses the available market-level data to simulate $a_{i1},...,a_{iT-1}$ and that uses data on demographic characteristics of smokers to control for unobserved heterogeneity in A_{i1}.

We begin by normalizing the level of the addiction stock in the first period to equal zero for all individuals ($A_{i1} = 0, \forall i$). This normalization does not restrict the initial stock to actually be zero.[15] A constant term is added to the utility function to absorb the average level of A_{i1}, and interactions between the constant and demographic characteristics are added to control for systematic heterogeneity in addiction.[16]

[13]If we were to assume that the stock does not fully depreciate, we would still have a specification that is conceptually similar to Equation (3) since consumers' choices are based on differences between the utility derived from an inside good and the outside good. We did experiment with specifications where the stock did not fully depreciate and found similar results.

[14] During the estimation we consider two alternative values for the discount rate, 0.6 and 0.8. We find that both lead to nearly identical values for the price coefficients that are the focus of our analysis.

[15] In some robustness tests, we let the stock of addiction be any number between zero and the maximum value of the stock of addiction (1+(1-δ)). Remarkably, this does not make a difference in the estimation results because the stock fully depreciates when an individual does not smoke in a period, and this is quite likely to happen at some point given how we simulate the data on the addiction stock.

[16]In an application to multiple metropolitan areas, one could also use area-specific fixed effects to control for variation in the initial stock across space, conditional on demographic characteristics.

In the second period, we insert $A_{i1} = 0$ into (3) to express the stock of addiction as $A_{i2} = a_{i1}$. Then market-level data on cigarette purchases are used to construct an empirical Bernoulli distribution for a_{i1}. For example, if the market share of the outside good (not smoking) was 10% in period 1, then the probability that individual *i* was a smoker is 0.90. The smoking probability is used to simulate the distribution of smoking decisions:

$$A_{i2} = a_{i1} = 1, \text{ if consumer } i \text{ chose to smoke in period 1.} \tag{4}$$
$$A_{i2} = a_{i1} = 0, \text{ if consumer } i \text{ chose not to smoke in period 1.}$$

This approach calibrates the share of individuals assigned to smoke to match the share of individuals observed purchasing cigarettes in our market-level data.[17] Put differently, we are modifying the BLP approach to simulation-based estimation by randomly assigning each simulated consumer to be a smoker or a non-smoker, based on the market share of the outside good in the previous period.

Finally, the market shares of the outside good in periods 2 through T-1, are used to define period-specific Bernoulli distributions for $a_{i2},...,a_{iT-1}$. For example, the moment condition used to simulate the decision to smoke in period *t* is

$$prob(smoking) = \frac{1}{I}\sum_{i=1}^{I} a_{it} = 1 - s_{0t}, \tag{5}$$

where s_{0t} denotes the market share of the outside good. The law of motion in (3) is used to combine independent random draws on $a_{1t},...,a_{It}$ from (5) with the existing values for $A_{1t-1},...,A_{It-1}$ to simulate $A_{1t},...,A_{It}$. Repeating this exercise each period produces a series for the stock of addiction that is "fixed", in the sense that it is calculated prior to the estimation and then treated the same as an exogenous demographic characteristic. A_{it} will be uncorrelated with ξ_{jt} because the law of motion in (3) defines addiction to be common to all packs. The simulated distribution of A_{it} will be market-specific, varying across both time and space. Variation in the stock of addiction will influence the predicted market shares of each pack. We choose the coefficient on addiction in the utility function

An alternative approach to controlling for the initial stock of addiction would be to use a simple moving average representation as in Arcidiacono et al. (2007).

[17] With this strategy, the data from period 0 only enter the estimation through the simulated stock of addiction. We do not estimate the structural parameters in period 0.

(φ) together with the remaining structural parameters to match predicted and observed market shares.

Our approach to simulating A_{it} is analogous to the more conventional random coefficient models of consumer behavior. In any given market, we typically see some consumers purchasing products with relatively high prices, or extreme levels of other attributes. In the absence of individual demographic data, it is common for the econometrician to explain these purchases using distributions of income, age, and other demographics generated from the Consumer Population Survey (e.g. BLP; Nevo 2001). Similarly, since we are unable to observe the personal smoking history of each consumer, we can explain their cigarette purchases by generating a distribution of addition from market-level data on past cigarette purchases combined with CPS data on smoker demographics.

4.2. Discussion

The discrete choice model in (2)-(5) generalizes the standard BLP specification to recognize that consumers may be addicted to a differentiated product. This allows us to make three extensions to the existing literature on cigarette demand and market power. First, unlike the previous studies of market power by Sumner (1981), Sullivan (1985), Ashenfelter and Sullivan (1987), and Raper et al. (2007), our description of demand is consistent with growing evidence that consumers are forward-looking with respect to price (e.g. Arcidiacono et al. 2007; Coppejans et al. 2007). Forward-looking behavior is one of the key implications of rational addiction theory. However, like Gruber and Köszegi (2001), we also recognize that consumers may have less than perfect foresight on the exact magnitude of future price changes. Our framework imposes the weaker condition of perfect foresight on *trends* in *near future* cigarette prices. Second, our structural model of the choice process acknowledges the addictive nature of cigarettes and also accounts for pack characteristics that affect consumer behavior but cannot be directly measured by the econometrician, such as advertising and brand image. Finally, by modeling the choice among differentiated cigarette packs, we can distinguish between price changes that arise from changes in conduct on the part of firms and price changes that arise from compensating behavior on the part of consumers (Barzel 1976; Evans and Farrelly 1998; Farrelly et al. 2004).

Overall, the framework in (2)-(5) offers an intermediate step between a static model of the demand for a differentiated product and a fully dynamic model of intertemporal choices made by addicted consumers. The principal difference between our framework and the fully dynamic models developed in theoretical work by Becker and Murphy (1988) and Gul and Pesendorfer (2007) is that the single-period utility function in (2) does not include a structural representation of the smoker's recognition that their future consumption will depend on present consumption decisions. Instead, this recognition is subsumed within the coefficient on p^{e}_{jt+1}.

Compared to a fully dynamic model, our framework has advantages and limitations. The advantages stem from its tractability. The specification in (2)-(5) is capable of quantifying two key features of rational addiction theory—reinforcement and forward looking behavior—without substantially increasing the computational burden of the BLP estimator. All of the parameters of the model are recovered from a single-stage simulated GMM estimator that uses repeated cross sections of market level data. Relative to BLP, the most significant added burden in this model is the need to develop separate instruments for current and future prices, as discussed in the next section.

In principle, developing a fully dynamic model would provide the means to overcome two limitations of our framework. First, our depiction of the choice process does not include a structural representation of changes in individual smoking intensity. As the stock of addiction grows, we might expect smokers to increase the number of cigarettes they smoke per day. This would be consistent with an upswing in the "cycle of addiction" predicted by Gul and Pesendorfer (2007). Second, as noted earlier, we do not have a structural representation for the smoker's realization that their current consumption decision will affect their future stock of addiction. Building this feature into a dynamic model would make it possible to investigate the intertemporal tradeoffs associated with a smoker's decision to purchase quitting aids such as nicotine replacement drugs.

It would be challenging to develop a fully dynamic estimable model of the brand and quantity choices simultaneously made by addicted forward-looking consumers. A likely starting point would be the dynamic models of consumer behavior developed recently by Hendel and Nevo (2006) and Gowrisankaran and Rysman (2009).[18] These models would have to be extended to formalize the connections between past, present, and future consumption that arise from a smoker's physical dependence on nicotine. To identify all of the structural parameters, one would probably need to obtain a long panel of micro data on individual smoking behavior. We leave these tasks for future research and shift our focus to identifying and estimating the parameters of the single-period utility function in (2).

[18] As a preliminary step, one might consider nesting our discrete choice model within a mixed discrete-continuous framework such as Hanemann (1984) or Hendel (1999).

5. Estimation and Identification

5.1. Estimation

Assuming the ε_{ijt}'s follow an *iid* Type I extreme-value distribution, and normalizing the utility from not smoking to equal zero, allows us to express the probability that individual *i* chooses brand *j* in period *t* as:

$$s_{ijt} = \frac{\exp\left(x_j\beta_i + \alpha_i p_{jt} + \gamma \ p_{t+1}^e + \varphi \ A_{it} + \xi_{jt}\right)}{1 + \sum_m \exp\left(x_m\beta_i + \alpha_i p_{mt} + \gamma \ p_{t+1}^e + \varphi \ A_{it} + \xi_{mt}\right)}. \tag{6}$$

Aggregating these probabilities over all individuals yields a set of predicted market shares, conditional on values for the structural parameters (θ) and unobserved pack characteristics (ξ_t). Berry (1994) and BLP illustrate how data on actual market shares can be used together with data on product characteristics and the distribution of consumer demographics to identify θ and ξ. Their estimation strategy is based on two-step simulated GMM, where the moment conditions are defined by treating ξ_{jt} as a structural error term and by using a contraction mapping to express it as a function of the taste parameters.

Petrin (2002) demonstrates that the taste parameters can be better identified by developing additional ("micro") moment conditions that match predicted and observed values for consumer demographics. For example, the probabilities in (6) can be aggregated over consumers to predict the average age and average income of smokers. θ can be chosen to minimize the difference between the predicted and true values for these statistics. Our micro moments are constructed using data from the Panel Study of Income Dynamics (PSID). From the PSID we collect information on the average age and average income of smokers in Tennessee.

Equation (7) shows our GMM objective function, which stacks moment conditions based on demographic characteristics, $D(\theta)$, and the BLP moment conditions, $\xi(\theta)$.

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\ \omega(\theta)'ZWZ'\omega(\theta), \qquad \text{where} \qquad \omega(\theta) = \left[\xi(\theta), D(\theta)\right]. \tag{7}$$

In the equation, Z is a matrix of instruments and W^{-1} is a consistent estimate of $E\left[Z'\omega(\theta)\omega(\theta)Z\right]$. We refer readers to BLP and Petrin (2002) for a full-fledged exposition of the GMM algorithm and use the remainder of this section to discuss identification.

5.2. Identification

In order to identify the structural parameters, we must address the possibility of correlation between the structural error term in the BLP-moment conditions and current and future prices. Since consumers and firms both observe ξ_{jt}, we would expect firms to set current prices that reflect these characteristics. Furthermore, if consumers' expectations about future prices depend on current period prices, then future prices will also be correlated with ξ_{jt}. Because prices are likely correlated over time, we will need two separate sets of instruments.

First consider the endogeneity problem with future prices. If future prices are a function of future unobservables, and future unobservables are correlated with current unobservables, then future prices will be endogenous. The MSA provides a unique opportunity to develop an instrumental variable capable of distinguishing the effect of expected price increases on current demand from the effect of current prices on demand. We treat the MSA as a quasi-natural experiment and define a dichotomous instrumental variable that is equal to 0 before the MSA, and equal to 1 after the MSA. The underlying idea is that the MSA was an exogenous event that changed the way smokers formed their expectations on future cigarette prices. Since the MSA imposed the same effective per-pack tax on all of the major cigarette manufacturers, it should be uncorrelated with unobserved pack characteristics, making the post-MSA indicator a valid instrument.

To investigate the identifying power of the post-MSA indicator, we follow the approach developed in the econometric literature on weak instruments (Bound et al. 1995; Staiger and Stock 1997). We begin by calculating the Staiger-Stock inverse F-statistic for excluding the MSA instrument from a "first-stage" regression of p^e_{jt+1} on all of the exogenous variables (pack characteristics and brand dummy variables). The resulting statistic is close to zero (1/F=0.0018), signaling that the MSA instrument has strong identifying power.[19] Two factors contribute to the low inverse F-statistic: (i) a large sample of scanner data (N=23,824), and (ii) strong correlation between p^e_{jt+1} and the MSA instrument ($\rho = 0.7466$). To see why the correlation is strong, recall that p^e_{jt+1} is simply an indicator variable for whether prices increase between periods t and $t+1$. After the MSA, price increases became much more common. As Figure 1 illustrates, prices were constant or declining before the MSA, and then started to increase rapidly after the

[19] More precisely, the inverse F-statistic implies that the finite sample bias associated with the instrument is approximately 0.18% as large as the bias associated with OLS estimation.

[20] Notice that while the year-to-year variation in the instruments is minimal before the MSA, there is considerable variation after the MSA. Most importantly, the MSA can be reasonably thought of

MSA.[20] This is consistent with our intuition that the MSA would have changed consumers' expectations about future trends in cigarette pricing.

Next, consider the endogeneity problem with current prices. To address this problem we construct a second set of instruments from first-order basis functions of pack characteristics. We used a Freedom of Information Act request to the Federal Trade Commission to obtain exact measures of tar, nicotine, and carbon monoxide for each pack.[21] Tar, nicotine, and carbon monoxide content are ideal instruments for price because they are continuous, they vary across brands, they reflect manufacturing costs, and they are not directly observed by consumers.

Consumers do have access to incomplete information about two of our three instruments, tar and nicotine. Their concentrations influence the advertised strength of each pack (regular or light) and the sensory experience of smoking. Tar, which affects the cigarette's flavor, is the total material captured on a filter pad when cigarettes are machine-smoked. Nicotine content determines the intensity of psychoactive reactions to smoke inhalation. Tar and nicotine concentrations vary substantially across different packs with the same advertised strength. For example, within the subset of "regular" strength packs tested in 2002, the coefficient of variation on tar levels was 0.17, and it was 0.18 for nicotine. Furthermore, the amount of tar and nicotine delivered tends to change over time. For the average pack in our data, tar and nicotine changed by 6.7% and 13.7% between 1993 and 2002. Since the exact concentrations of tar and nicotine cannot be observed (or experienced without smoking that pack) they do not enter the consumer's choice process in our main specification of the empirical model.[22]

We follow BLP in using first-order basis functions of tar, nicotine, and carbon monoxide as instruments. We construct nine instruments: the pack's tar, nicotine, and carbon monoxide content; the sum of the tar, nicotine, and carbon monoxide content of all packs produced by the firm; and the sum of the tar, nicotine, and carbon monoxide content of all packs produced by all other firms. As explained in BLP, basis functions of product characteristics provide valid instruments for price even if each characteristic enters the consumer's utility function. Intuitively, the profit-maximizing price a firm will charge for each product will depend on the characteristics of the competing products that it sells and the characteristics of competing products sold by other firms.

as a quasi-experiment. Much of the identification is from the months and years around the MSA.

[21] Our request covered the years 1999-2002. For the earlier years in our study, data on the chemical concentrations were publicly available. For example, see Federal Trade Commission (2000).

[22] As a robustness check, we also estimate models where tar, nicotine, and carbon monoxide enter utility directly. This has almost no impact on our estimates for the price coefficients in the utility function. Results are provided in the supplemental Appendix. See also Footnote 32.

The year-to-year variation in the basis function instruments is minimal. As in BLP, we assume these changes are exogenous in the sense that the firms do not choose prices and characteristics simultaneously. To develop some intuition for the empirical power of these instruments we ran a reduced-form first-stage regression. After controlling for pack characteristics and brand dummy variables, the nine instruments explain 44% of the remaining variation in prices. Likewise, the inverse F-statistic for weak instruments (Staiger and Stock, 1997) is less than 0.01 suggesting that finite sample bias is not a major concern.

6. Data

The model was estimated by combining three types of data: (1) cigarette sales in Knoxville, TN for five stores that are part of a major supermarket chain, (2) a comprehensive set of observable characteristics describing individual cigarette packs, and (3) data on the demographic characteristics of smokers and non-smokers in the Knoxville metropolitan area, as reported in the Census of Population and the Tobacco Use Supplement to the Consumer Population Survey. This section describes how we combined the three data sets.

6.1. Cigarette Sales

We obtained weekly scanner data on cigarette sales in five supermarkets in the Knoxville metropolitan statistical area from October 1993 through December 2002. A "market" was defined as a store-quarter combination based on our observation that nominal price changes occur about once every 90 days. With 5 stores, 37 quarters, and between 109 and 148 different packs and cartons in each market, we have 185 markets and 24,419 product-store-market observations.[23] All of the packs belong to 26 different premium and discount brands. We focus on the six largest manufacturers, Phillip Morris, R.J. Reynolds, Brown and Williamson, American Tobacco Company, Lorillard, and Liggett.[24] Together, these firms accounted for more than 90% of U.S. cigarettes sales each year during our study period. We assume their pricing decisions were unaffected by the behavior of the smaller manufacturers responsible for the remaining sales.

Our scanner data coincide with national pricing trends. Figure 1 compares the time trend in the Knoxville data with the average state price of premium cigarette packs net of federal and state taxes, and net of the per/unit effective tax

[23] To keep the estimation process feasible we discarded packs with negligible market shares and atypical characteristics. In particular, we dropped packs which are unfiltered, "medium" strength, "ultima" strength, longer than 120 millimeters, or packaged in a quantity other than a pack or carton. The remaining 24,419 observations that comprise the data used to estimate the model account for more than 85% of total sales.

[24] American Tobacco Company merged with Brown and Williamson in 1995.

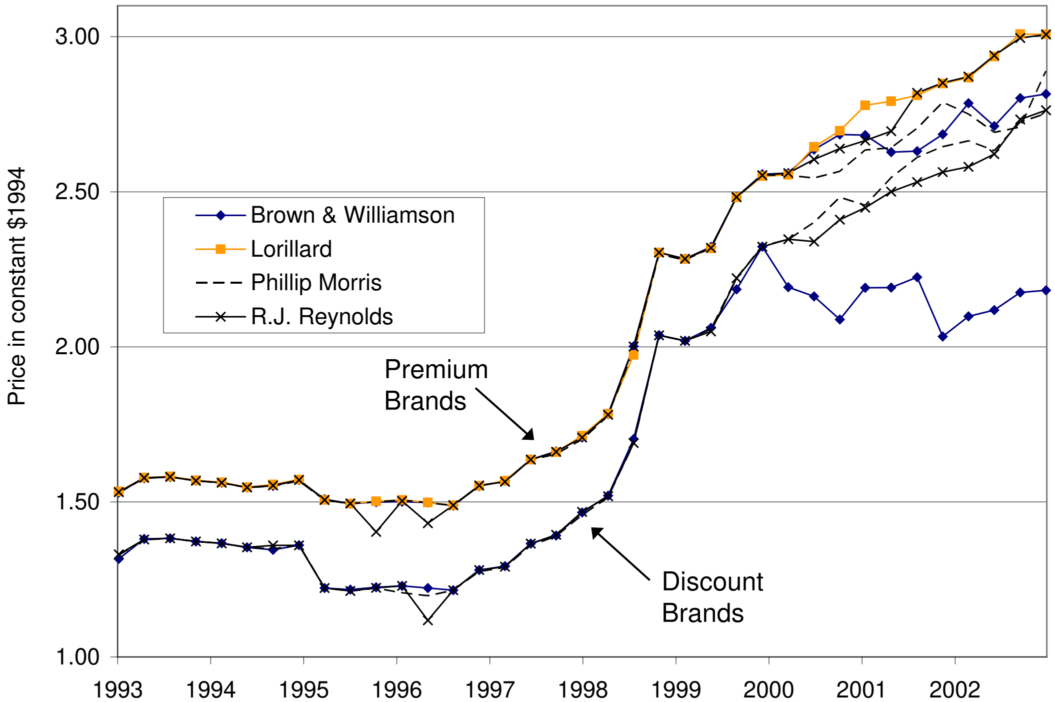
imposed by the MSA (from Table 1). Following "Marlboro Friday" in April 1993, the average price of cigarettes dropped substantially and remained relatively constant until the first agreements between the cigarette firms and the states were signed in July, 1997. Since then, cigarette manufacturers have raised unit prices by far more than the increase in unit taxes. After taxes, the real price per pack increased by an average of 10% *per year* between 1997 and 2002.

TABLE 2: Cigarette Market Shares in Knoxville and the United States, 1996

Firm	Brand	United States			Knoxville scanner data		
		total	discount	premium	total	discount	premium
				Market Share by Firm			
Philip Morris	All	47.8	7.5	40.3	51.1	7.8	43.3
RJ Reynolds	All	24.6	9.1	15.5	37.0	6.8	30.2
Brown & Williamson	All	17.2	9.8	7.4	8.9	1.7	7.1
Lorillard	All	8.4	0.5	7.9	2.9	0.0	2.9
Total: 4 Firms	All	*98.0*	*26.9*	*71.1*	*99.9*	*16.3*	*83.6*
				Market Share for Premium Brands			
Philip Morris	Marlboro			32.3			32.7
Philip Morris	Virginia Slims			2.4			6.3
Philip Morris	Merit			2.3			2.4
RJ Reynolds	Winston			5.3			13.4
RJ Reynolds	Camel			4.6			3.4
RJ Reynolds	Salem			3.6			5.4
Brown & Williamson	Kool			3.6			3.1
Brown & Williamson	Carlton			1.3			2.6
Brown & Williamson	Pall Mall			1.1			0.4
Lorillard	Newport			6.1			0.7
Lorillard	Kent			0.8			1.4
Lorillard	True			0.4			0.2

The Knoxville data are also fairly representative of national market shares across firms and brands. Table 2 compares the share of sales for the top three premium brands sold by each of the four largest firms, using national data for 1996 from the Federal Trade Commission. At the firm level, the scanner data have more sales for Philip Morris and R.J. Reynolds, and less for Brown & Williamson and Lorillard. At the brand level, *Winston*, *Virginia Slims*, and *Salem* have disproportionately large market shares in the scanner data, while the market shares for *Camel* and *Newport* are disproportionately small.

**FIGURE 2: Average Price of a Pack of Cigarettes.
Premium and Discount Brands, by Firm**



Our data reinforce the stylized fact that cigarette firms do not price differentiate within brands. A pack of *Marlboro* Full Flavor 100's is virtually always priced the same as a pack of *Marlboro* Light 120's, for example. However, manufacturers do price brands differently. Figure 2 shows the average price charged for premium and discount brands by each of the four largest manufacturers during our study period. Between "Marlboro Friday" and the second quarter of 2000, almost all the price variation occurred *between* the premium and discount segments of the market, making it appear as if there are only two price trends in the figure. During this period, the premium packs that comprise the more expensive price series cost between 19 and 30 cents more than the discount packs. The only major exception to this pricing pattern occurred during 1996, when R.J. Reynolds appeared to initiate a price decrease in the premium and discount markets, which was followed by a slight decrease in the price of Phillip Morris's discount brands. Then, beginning in the third quarter of 2000, the cigarette manufacturers started charging different prices within the premium and discount segments of the market. This variation will play an important role in identifying cross-price elasticities during the estimation.

6.2. Pack Characteristics

For each individual pack in our data, we collected information on cigarette length (80mm or 100mm); advertised strength (regular or light); whether they are mentholated; whether they are packaged in crush-resistant boxes; and whether they are sold in cartons. These are the observable pack characteristics that enter our empirical specification for utility. Table 3 shows means and standard deviations for these characteristics, as well as the concentrations of tar, nicotine, and carbon monoxide that we use to construct instrumental variables. Notice that tar, nicotine, and carbon monoxide vary substantially. Most of this variation occurs between packs.

TABLE 3: Summary Statistics for Pack Characteristics

Variable	1993-2002	Before MSA	After MSA
$price_t$	1.88	1.42	2.43
	(0.54)	(0.14)	(0.31)
menthol	0.40	0.39	0.41
	(0.49)	(0.49)	(0.49)
light	0.61	0.63	0.60
	(0.49)	(0.48)	(0.49)
length100	0.61	0.62	0.60
	(0.49)	(0.48)	(0.49)
carton	0.42	0.43	0.42
	(0.49)	(0.50)	(0.49)
tar	10.21	10.01	10.34
	(4.26)	(4.36)	(4.15)
nicotine	0.80	0.77	0.83
	(0.29)	(0.29)	(0.29)
carbon monoxide	11.08	10.98	11.06
	(4.20)	(4.41)	(3.94)
# observations	24419	8545	10463

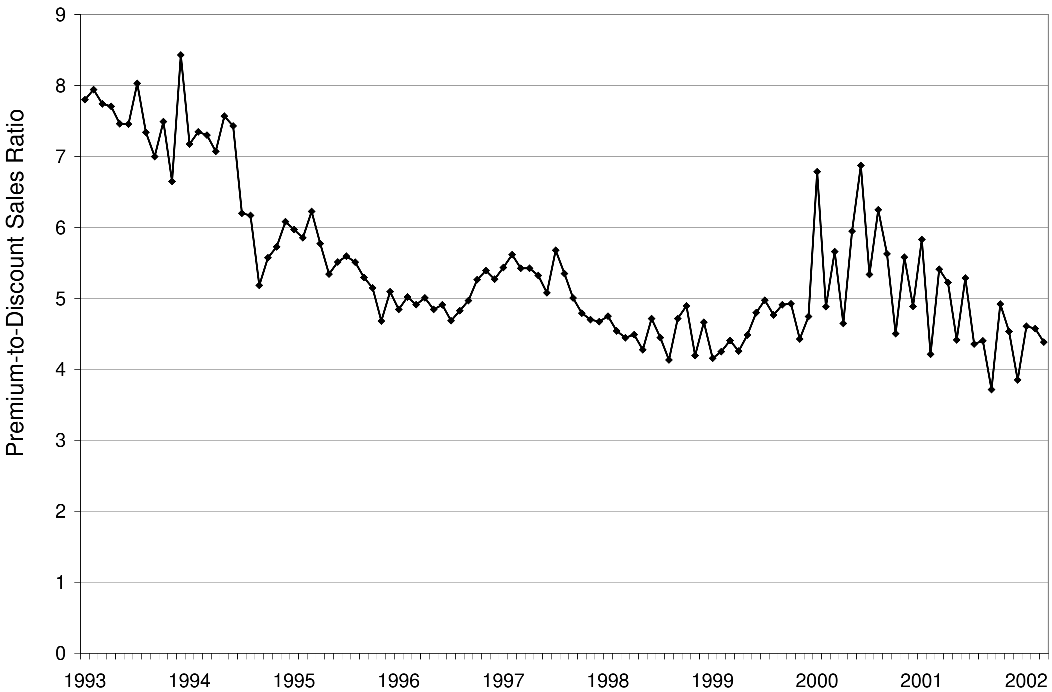
While there is very little temporal variation in pack characteristics, the average pack price increased by a dollar during the first few years following the MSA. Barzel (1976) provides one potential explanation for this effect. He hypothesizes that as the per-unit tax on a set of heterogeneous goods increases, consumers will reduce their consumption and substitute toward untaxed quality attributes, which, in turn, will increase average product quality and further increase the average market price. Barzel's hypothesis is relevant for the MSA because, like state and federal cigarette taxes, the volume adjustment to the MSA does not vary with pack characteristics. Thus, one might expect the large price increase in Table 3 to stem partly from consumers reacting to a change in relative prices by smoking less and substituting toward premium packs, which they perceive to provide higher quality tobacco. We used our scanner data to investigate the empirical magnitude of this effect.

6.3. Does the Increase in Average Prices Reflect a Shift toward Quality?

Figure 3 illustrates the time path for the premium-to-discount sales ratio in our scanner data. Between the start of the "Marlboro Friday" price war and the signing of the MSA, the share of premium packs decreased steadily amid monthly fluctuation. Following the MSA, the average price of both premium and discount packs increased by 83 cents between October 1998 and October 2000. Multiplying this constant price increase by the marginal percentage change reported by Sobel and Garrett (1997) would imply a 27% increase in the market share of premium packs. We observe a somewhat smaller increase: 12%. Then, between October 2000 and December 2002, the price of premium packs increased by 16 cents more than the price of discount brands, which helps to explain why the market share of premium packs decreased during this period. By the end of 2002, the market share of premium packs was virtually the same as its pre-MSA level in early 1997. Thus, Barzel's hypothesis does not explain the large increase in the average price of cigarettes in our scanner data.

One might be concerned that our data are not nationally representative. Nevertheless, a quick calculation allows us to dispense with quality-shifts as a major source for the increase in national average prices. Multiplying the 44-cent effective tax imposed by the volume adjustment to the MSA by the marginal result from Sobel and Garrett's national analysis, would imply a 14.6% increase in the market share of premium packs. Given the 50-cent price differential between premium and discount packs, the predicted increase in the market share of premium brands would imply a 7-cent increase in the national average price—far below the actual price increase.

FIGURE 3: Premium-to-Discount Sales Ratio in Knoxville, TN: 1993-2002



6.4. Consumer Demographics and Market Size

We used data from the 12 Tobacco Use Supplements to the Consumer Population Survey that were available during our study period to calculate the average age and income of smokers in the Knoxville metropolitan statistical area.[25] These statistics formed the basis for the "macro" side of the moment conditions used during the estimation to match predicted and observed demographic characteristics of smokers. Aggregating over all the CPS data, the average smoker was 41 years old with an income of $32,511 in constant 1994 dollars.

Since our scanner data do not identify individual consumers, we used GIS software and tract-level data from the 2000 Census of Population to match each supermarket with the joint distribution of age and income for its most likely customers. To do this we overlaid "shopping zones" on Census tracts in the Knoxville metropolitan area and took weighted averages of age and income over the adult population between 18 and 70, living in each shopping zone. Shopping zones were defined using a 2.8 mile radius around each store, which was found by Ohls et al. (1999) to be the average distance that shoppers travel to supermar-

[25] The demographic characteristics of the sample did not change substantially over the twelve-year period. The effects of the demographic characteristics are identified by cross-sectional variation across the areas where the supermarkets are located.

kets.[26] The distribution of age and income for the population living in each store's shopping zone is used to construct the "micro" side of the moment conditions based on consumer demographics.

The shopping zones were also used to define the market size for each store and, therefore, the market share of the outside good. Our definition of the market size starts from the adult population between 18 and 70, living in the shopping zone during the 2000 Census. We take this selected population and adjust it using the following three facts: (1) According to the Panel Study of Income Dynamics, 20% of Tennessee's adult population smokes or smoked at some point in their lives; (2) the average smoker smokes 15 cigarettes per day (75% of a pack); and (3) the type of retailer that provided our data accounts for approximately 10% of total tobacco sales (Gale et al. 2000).[27] Thus, the market size for each store was defined by multiplying 20% of the adult population living in the corresponding shopping zone in the year 2000, by 0.75 (packs per day) by 90 (days in a quarter) by 0.10 (of total cigarette purchases). Finally, to account for temporal variation in the demand faced by individual stores, we multiply the potential market size by an index that is equal to the number of consumers that visited a store in a given quarter-year divided by the number of consumers that visited the same store in the first quarter of 2000.[28]

7. Demand Estimates

7.1. Parameter Estimates

Table 4 reports the parameter estimates from seven alternative specifications for the model. The first two columns report the results from the simplest specification where consumers are treated as if they are myopic and cigarette addiction does not influence their current smoking decisions. In the first column, the probability of smoking is assumed to depend only on prices and whether the cigarettes

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[26] Some of our stores were slightly less than 2.8 miles apart or slightly less than 2.8 miles from another store in the same supermarket chain. We addressed this overlap by truncating the shopping zones to remove intersections. Since the resulting shopping zones do not overlap perfectly with census tracts, the demographic data were attached to each zone based on the assumption that people are uniformly distributed within each tract.

[27] One concern is that people who purchase cigarettes at supermarkets may be an unusual group of smokers. For example, price-sensitive smokers or heavy smokers may be willing to search aggressively to find low prices. Alternatively, they may be willing to travel to other, low-tax jurisdictions such as North Carolina, which tends to have low cigarette taxes, and is near Knoxville. While we recognize the importance of this concern, we do not have a way to quantify its empirical significance. This is also a limitation in the well known study by Chevalier et al. (2003).

[28] We tested the robustness of our approach to defining the market by estimating the model under alternative definitions for market size. For example, we multiplied the maximum sales observed for each store during any quarter by 1.2, 1.5, and 2. Increasing the size of the market decreased the own-price elasticities slightly, without affecting the qualitative results.

are mentholated, light, 100 millimeters long, and sold as cartons. Smokers appear to prefer cigarettes that are less than 100 millimeters, light, un-mentholated, and sold in individual packs. While these directional effects are consistent throughout the specifications in the table, their magnitudes change substantially when brand dummy variables are added to the model.

TABLE 4: Parameter Estimates from Alternative Specifications

	1	2	3	4	5	6	7
$price_t$	-0.611	-0.755	-0.745	-0.774	-0.607	-0.619	-0.606
	(0.015)	(0.014)	(0.017)	(0.026)	(0.083)	(0.076)	(0.081)
$Eprice_{t+1}$			-0.018	-0.062	-0.112	-0.107	-0.111
			(0.019)	(0.033)	(0.065)	(0.061)	(0.064)
menthol	-0.335	-0.661	-0.661	-0.659	-0.656	-0.656	-0.656
	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)
light	0.019	0.149	0.148	0.147	0.145	0.145	0.145
	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
length>=100mm	-0.173	-0.089	-0.089	-0.089	-0.091	-0.091	-0.091
	(0.017)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)
carton	-1.649	-1.866	-1.864	-1.871	-1.834	-1.837	-1.834
	(0.017)	(0.015)	(0.015)	(0.017)	(0.022)	(0.021)	(0.022)
A_{it}					0.897	0.849	0.903
					(0.538)	(0.557)	(0.514)
income						0.003	0.004
						(0.030)	(0.030)
age						-0.007	-0.001
						(0.113)	(0.113)
IV: MSA instrument	no	no	no	yes	yes	yes	yes
IV: tar/nic/co instruments	no	no	no	yes	yes	yes	yes
discount rate (δ)	---	---	---	---	0.6	0.6	0.6
brand dummy variables	no	yes	yes	yes	yes	yes	yes
new smokers & quitters	no	no	no	no	no	no	yes
R-squared	0.31	0.49	0.49	0.49	---	---	---
GMM	---	---	---	---	127.23	162.30	161.05
Median Price Elasticity	-1.03	-1.28	-1.26	-1.31	-1.12	-1.14	-1.11
pre-MSA	-0.92	-1.13	-1.12	-1.16	-0.86	-0.87	-0.85
post-MSA	-1.52	-1.87	-2.00	-2.07	-1.35	-1.34	-1.31

Brand image is perhaps the most important pack characteristic we are unable to observe. Familiar characters such as *Joe Camel* and *The Marlboro Man* may create an image in consumers' minds that affects the utility they derive from smoking those brands.[29] Similarly, brands that offer promotions such as "Camel Cash" which can be redeemed for clothing, sporting goods, and memorabilia, may make those brands more attractive. To control for branding, we added dummy variables for the 26 brands in our data to the simple myopic model. The results are reported in Column 2. Adding brand dummies decreases the coefficient on price by 23%, increases the coefficient on length by 49%, decreases the coefficient on menthol by 97%, and leads to an order-of-magnitude increase in the coefficient on light. Controlling for brand effects is clearly important.

Column 3 generalizes the myopic model to recognize that smokers may be forward looking in the sense that they recognize that their choice today will affect their desire to smoke tomorrow. The resulting coefficient on the future price variable has the expected negative sign, but is not statistically different from zero.

Column 4 reports the results after adding the MSA instrument for future prices and the instruments for current price constructed from basis functions of the tar, nicotine, and carbon monoxide content of each pack.[30] Moving to an IV specification decreases the future price coefficient from -0.018 to -0.062, making it statistically significant. A negative relationship between current consumption and an expected increase in future prices is consistent with forward-looking behavior on the part of consumers. Thus, the MSA instrument delivers results that are consistent with the predictions of rational addiction theory.[31] Likewise, the coef-

[29] As noted earlier, advertising expenditures are the main difference between premium and discount brands. Firms spent $11.2 billion on advertising in 2001, despite numerous restrictions on the allowable forms of advertising (Federal Trade Commission, 2003).

[30] F-statistics of the excluded instruments from the first-stage regressions are F=560 for the MSA instrument and F=6536 for the set of instruments based on tar, nicotine, and carbon monoxide content of each pack. The supplemental Appendix reports the results from adding each set of instruments incrementally.

[31] A potential concern with the specification in Column 4 is that our dichotomous MSA instrument confounds changes in expectations about future prices with the direct effect on utility of changes in advertising and public health initiatives legislated by the MSA. Fortunately, the incremental nature of the MSA settlement provides an opportunity to test this hypothesis. There was a lag between when the first settlement payments were made (July 1997) and when the agreement on advertising restrictions and public health initiatives was completed (November 1998). With this in mind, we ran an additional IV specification with two indicator variables. The first indicator turns on when the initial settlement payments are made (3rd quarter 1997) and the second turns on when the advertising restrictions and funding for public education become operational (4th quarter 1998). Both indicators enter as explanatory variables during the first stage, but only the second indicator is included in the utility function in the second stage. This produces almost no change in our estimated coefficient on future prices. It decreases from -0.062 to -0.079, relative to Column 4, and the two coefficients are within half a standard error of each other. Full results are reported in the supplemental Appendix.

ficient on current price decreases from -0.745 to -0.774.[32] While the magnitude of this change may seem small, it is important to keep in mind that brand dummies already capture all brand-specific dimensions of unobserved quality. Overall, the results in Column 4 imply that smokers consider both current prices and future price trends in their current smoking decisions, but the relative magnitudes of these two effects suggest that current prices are what drive behavior.

The last three columns of the table present the most general version of the model where smokers' current choices depend on their stock of addiction and on their expectation for whether price will increase in the near future.[33] All three specifications are based on a quarterly discount rate of 0.6.[34] They differ in the way we control for demographic characteristics.

Column 5 reports the results from the baseline model without smoker demographics. The coefficients on the current price and the expected future price trend are both negative, suggesting that the long-run demand for cigarettes will be more inelastic than the short-run demand. This finding coincides with the existing empirical literature on rational addiction (Chaloupka 1991; Becker et al. 1994). Not surprisingly, we also find that the stock of addiction has a positive effect on the utility from smoking. Thus, our econometric results are consistent with two of the main implications of rational addiction theory ($\varphi > 0$ and $\gamma < 0$).

Introducing demographic characteristics complicates the estimation process because, as consumers age, their income changes. We incorporated both features of this dynamic process into our simulation. This process began with an initial sample of consumers for each of the five stores in period 1. Then, to adjust income accordingly, we aged this distribution of individuals each year and used the discrete approximation to the joint distribution of age and income available from the Census data for our shopping zones. For example, suppose a representative smoker enters our sample at age 43 with income in the 54th quantile of the distribution for people between the ages of 35 and 44. When that individual turns

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[32] This result is robust to alternate IV specifications. For example, adding tar, nicotine, and carbon monoxide as variables that enter utility directly decreases the price coefficient to -0.809. Adding retail gasoline prices as an instrument produces a coefficient of -0.796. The rationale for using gas prices is that the large (up to 60%) changes in real gasoline prices have income effects that might influence prices changed by profit-maximizing cigarette firms. Full results from these models and other robustness checks are reported in the supplemental Appendix.

[33] For each specification, we solve Equation (7) using a simulated annealing algorithm with a Nelder-Mead non-derivative search. Starting values were defined by the results from a simple logit model. Simulated annealing tests randomly-chosen points against the current function value on every iteration of the GMM objective function. This increases the robustness of the optimization procedure to situations where there may be multiple local optima.

[34] Increasing the discount rate to 0.8, increases the magnitude of the coefficient on addiction, but has a negligible effect on all other coefficients and demand elasticities. These results are reported in the supplemental Appendix.

44, their income is unchanged. However, when they turn 45, their income is redrawn based on the 54^{th} quantile of the income distribution for people between the ages of 45 and 54.

Columns 6 and 7 report the parameter estimates from two versions of the model that included interactions between a constant and demographic characteristics.[35] Since utility from the outside good is normalized to zero, the coefficients on age and income reflect their influence on the probability of smoking. The difference between the models in Columns 6 and 7 lies in their treatment of consumers who choose the outside good. The results reported in Column 6 are based on using the same set of consumers throughout the simulation. In this case, smokers who maximize their utility by choosing the outside good remain in the sample for the following period, at which point they may relapse or they may continue to choose not to smoke cigarettes. The version of the model summarized in Column 7 replaced these "quitters" with new, 18-year old smokers. While the signs of the coefficients imply that consumers who are younger and/or wealthier are more likely to be smokers, neither effect is statistically different from zero.

7.2. Elasticities

The last two rows of Table 4 report the median own-price elasticity for an individual pack before and after the MSA. These elasticities are "short-run" in the sense that they are calculated holding future prices constant. As we would expect, our estimates for pack-level elasticities are much smaller than previous estimates for *industry*-level elasticities which treat cigarettes as a homogenous product. For example, Becker et al. (1994) report short-run elasticities for the *industry* that range from -0.36 to -0.47 and Evans and Farrelly (1998) report values between -0.15 and -0.35. In comparison, when we account for addition in the last three columns of table 4, our estimates for the median *pack*-level elasticity range from -0.85 before the MSA to -1.35 after the MSA. Because we define cigarettes as a differentiated product, our estimates reflect the likelihood that some smokers who face a unilateral increase in the price of their favorite pack will simply switch

[35] Further generalizations to the depiction of preference heterogeneity did not produce significant results. Random taste parameters (v_i) were found to be economically unimportant and statistically insignificant. Meanwhile, including a full set of interactions between pack characteristics and demographic characteristics led to statistically insignificant and economically implausible estimates (e.g., positive coefficients on price). This may reflect a low signal-to-noise ratio in our estimates for consumers' (unobserved) demographic characteristics. That is, despite our best efforts, the process of constructing the shopping zones may have failed to capture the complexity of actual shopping patterns and the relevant substitution possibilities. Another possibility is that there is too little variation in the distribution of consumer demographics between the five geographic markets and within each geographic market over time, for us to be able to identify the extent to which tastes vary with demographics.

to a different pack rather than smoke less. Switching to a different pack may mean switching to a different pack within the same brand, or it may mean switching to a different brand entirely. The notion that smokers are less than perfectly brand-loyal is consistent with Sobel and Garrett's (1997) finding that an increase in the relative price of discount brands leads to a substantial increase in the market share of premium brands. Likewise, Evans and Farrelly (1998) present evidence that smokers compensate for tax increases by switching to cigarettes with higher concentrations of tar and nicotine. This could mean switching to a different brand or switching between packs within a single brand (moving from Marlboro lights to regular Marlboros, for example).

Perhaps the most significant result in Table 4 is that when we account for addiction in the last three columns, our estimates imply that the median pack demand was *inelastic* prior to the MSA. Setting price on the inelastic portion of the market demand curve is inconsistent with a profit-maximizing pricing strategy in a static differentiated-product oligopoly. However, it is consistent with the "Marlboro Friday" price war. Firms may have been setting prices close to marginal cost during this period.

Following the MSA, firms set prices that correspond to a more elastic portion of the demand curve. All of our specifications with addiction indicate a large decrease in the median elasticity, with firms setting prices on the elastic portion of the demand curve following the MSA. Together, the patterns of pre-MSA and post-MSA pricing are consistent with the idea that the MSA acted as a coordinating device for cigarette firms to end the Marlboro Friday price war and collectively raise prices.

8. Inference on Firm Behavior

To further investigate how the MSA changed the nature of competition in the cigarette industry, we compare actual price trends with the prices that would be charged under a variety of alternative pricing rules, given our demand estimates. First, we infer the marginal cost of producing a pack of cigarettes. Then, we ask the following question: given the choices that firms make in future periods, what behavioral model would best explain the choices they make in the current period? This revealed preference logic maintains that firms make equilibrium choices at each point in time.

Table 5 presents the price trend we aim to explain—the annual median price of a pack of cigarettes in the years following the MSA. The median price was essentially constant between 1994 (\$1.46) and 1997 (\$1.43), and then grew by more than a dollar between 1997 and 2002. The remainder of Table 5 presents the baseline results from our analysis. Columns 1, 2, and 3 are constructed under the maintained assumption that firms compete. Columns 4, 5, and 6 are constructed under the assumption that firms collude. Each column shows the prices that we would predict under a particular pricing rule, conditional on the demand estimates reported in Column 5 of Table 4. 95% confidence intervals on the predicted prices were computed and are provided in brackets. After formalizing the firm's profit maximization problem, we explain each of the rules used to predict prices and interpret the corresponding results. To evaluate the robustness of results, we repeat the analysis after replacing our baseline estimates for marginal costs with an alternative measure of accounting costs.

8.1. The Firm's Profit Maximization Problem

We envision a market with N_t firms, denoted by $f=1,\ldots, N_t$, each of which produces some subset F_{ft}, of the J_t products. Let mc_{jt} denote the marginal cost of product j in period t and let the size of the market be denoted by M_t.[36] Firm f chooses the prices of its products $j \in F_\tau$, and $\tau = 0,\ldots,\infty$ to maximize its discounted stream of future profits:[37]

$$\Pi_f = \sum_{\tau=0}^{\infty} \beta^\tau \sum_{j \in F_\tau} \left(p_{j\tau} - mc_{j\tau}\right) s\left(p_{j\tau}\right) M_\tau \,. \tag{8}$$

Fixed costs are omitted for simplicity since they would drop out of the first order conditions. We also assume that firms have perfect foresight of future input prices.[38] As Roberts and Samuelson (1988) first noted, the assumption of perfect foresight on input prices seems reasonable for the cigarette industry partly due to the long-standing price support program for tobacco.[39]

In order to use (8) to predict equilibrium prices, we must first provide data on marginal costs. In previous applications, marginal cost has either been esti-

[36] For sake of simplicity, we continue to omit the subscript for a market. Recall that a market is defined as a store-year-quarter triplet.

[37] Sumner (1981), Sullivan (1985), and Ashenfelter and Sullivan (1987) assume that each state-year observation they use is an independent market. In particular, states and years with different excise tax rates give an incentive to cigarette manufacturers to charge different prices. We make the same assumption in our analysis, and we assume that the cigarette manufacturers choose their Tennessee prices independently of their choices in other states. Thus, our first order conditions do not incorporate the effect of price choices in Tennessee on sales in other states. In addition, we follow the mainstream empirical industrial organization literature (e.g., Nevo 2001), and assume that the retailers' margins are determined exogenously to our model.

[38] This assumption is not uncommon in empirical studies of dynamic behavior. For more discussion on the difference between models with perfect foresight and model where agents form rational expectations, see Judd (1998) and references therein.

[39] While the price support program recently expired, the legislation proposing the tobacco quota buyout that ended the program was not introduced to Congress until 2004. It would have been difficult for firms to anticipate this event during our study period, which ended two years earlier.

mated (BLP) or inferred under an equilibrium assumption Nevo (2001). Because we are unable to observe firms' marginal cost directly, and therefore need to estimate their marginal cost, we exploit the fact that the cigarette manufacturers were involved in a price war between 1993 and 1997. More precisely, we treat the minimum price charged for each pack from 1994 through 1996, as the marginal cost of producing that pack. Notice that this definition of marginal cost includes taxes. Net of taxes, we find a marginal cost that, on average, is equal to 73 cents for discount brands and 1 dollar for premium brands.

We find it highly unlikely that marginal costs increased substantially after 1996. This follows from two observations. First, the real price of raw flue-cured tobacco was virtually unchanged between 1997 and 2002. While the nominal price of flue-cured tobacco increased from $1.72 per pound in 1997 to $1.85 per pound in 2002, deflating these figures by the producer price index for finished goods implies a 1 cent increase in year 2002 dollars. Second, the cost of capital in the tobacco industry declined between 1998 and 2003.

8.2. Pricing Behavior in a Static Nash-Bertrand Oligopoly

We begin our analysis of firm behavior from the simplest possible model where the discount rate in the firm's maximization problem is set to zero so that firms behave as a static Bertrand-Nash oligopoly. This is a common assumption in the literature (e.g. Bresnahan 1987; BLP 1995; Nevo 2001; Petrin 2002). For a market organized as a static Bertrand-Nash oligopoly, the price p_j of any product *j* produced by a profit-maximizing firm *f* must satisfy the Jx1 vector of first order conditions in equation (9).

$$s_j(p_t)+\sum_{r\in F_{f,t}}(p_{r,t}-mc_{r,t})\frac{\partial s_r(p_{jt})}{\partial p_{jt}}=0\,. \tag{9}$$

The market share of the j^{th} product (s_{jt}) is a function of the prices charged for all the products in the market. Equation (9) can be solved for a vector of markups over marginal cost by defining $E_{jrt}=\partial s_{rt}/\partial p_{jt}$, $j,r=1,...,J$, and Ω_{jrt} $=\Omega^*_{jrt} * E_{jrt}$, where

$$\Omega^*_{jrt}=\begin{pmatrix}1, \text{ if } \exists f:(r,j)\subset F_{ft}\\ 0, \quad \text{otherwise}\end{pmatrix}.$$

As in Bresnahan (1987) and Nevo (2001), Ω_t^* is matrix of indicator variables which relate each product to its producer. For example, with single-product firms, Ω_t^* would be the identity matrix. Equation (10) expresses the first order conditions as a function of the ownership matrix in order to define the markup above marginal cost for all of the *J* products in the market.

$$p_t - mc_t = \Omega_t^{-1} s(p_t). \tag{10}$$

Given our data on the marginal cost of producing cigarettes, Equation (10) implicitly defines the vector of prices that would be charged by a static Bertrand-Nash oligopoly in equilibrium.

Equation (10) allows us to predict the prices that would be charged by firms in a static Nash-Bertrand oligopoly. Specifically, we use numerical methods to solve the system in (10) for p_t, given our point estimates for the demand parameters from Column 5 of Table 4.[40] Then we repeat this process using a bootstrapping procedure to solve for 95% confidence intervals on our predictions for Nash-Bertrand prices. If actual prices fall outside this range, we reject the null hypothesis that firms behave as a static Nash-Bertrand oligopoly.

Column 1 of Table 5 compares predicted and actual prices. The predicted prices are far above the observed prices in every year. For example, in 2002, the lower bound on the confidence interval for the predicted median price (\$3.17) was well above the actual median price (\$2.66). This evidence leads us to reject the hypothesis that firms played a static Nash-Bertrand game after the MSA.

8.3. Pricing Behavior in a Two Period Nash-Bertrand Oligopoly

Now consider the case where firms maximize their discounted stream of future profits but only look ahead one period. In this model of bounded rationality, firms set prices in period *t* given their perfect foresight on the prices that will be charged in period $t+1$. To illustrate this, let p_{jt}^* denote the equilibrium price for product *j* at time *t*. Then, firm *f*'s first order condition corresponding to the choice at time *t* for product *j*, can be written as:

$$s_j(p_t) + \sum_{r \in F_{f,t}} (p_{r,t} - mc_{r,t}) \frac{\partial s_{r,t}(p_t)}{\partial p_{j,t}} + \beta \sum_{r \in F_{f,t+1}} (p_{r,t+1}^* - mc_{r,t+1}) \frac{\partial s_{r,t+1}(p_{t+1}^*)}{\partial p_{j,t}} = 0. \tag{11}$$

[40] We use a rootfinding algorithm to solve for the *p*-vector that satisfies (10) under each set of parameter estimates reported in Table 4.

The first two terms are the same as in the static Nash-Bertrand case. The third term introduces the dynamics. To interpret the dynamic term, consider the effect of a current period price increase on an individual's probability of purchasing pack *r* next period:

$$\frac{\partial s_{i,r,t+1}}{\partial p_{jt}} = \frac{\partial s_{i,r,t+1}}{\partial A_{i,t+1}} \frac{\partial A_{i,t+1}}{\partial p_{j,t}} < 0, \quad \text{given } \phi > 0,\ \alpha < 0,\ s_{ijt} > 0 \ \ \forall \ \ j,t. \tag{12}$$

The firm knows that a price increase today has the potential to decrease an individual's stock of addiction tomorrow by decreasing their probability of smoking today. This is reflected in the second term to the right of the equality in (12): $\partial A_{i,t+1} / \partial p_{j,t}$. The firm also knows that a decrease in the individual's stock of addiction tomorrow will decrease their probability of smoking pack *r* tomorrow. This is reflected in the first term to the right of the equality in (12): $\partial s_{i,r,t+1} / \partial A_{i,t+1}$. It is straightforward to demonstrate that the product of these two partial derivatives is strictly negative given the specification for utility in (2), positive market shares, $\phi > 0$, and $\alpha < 0$. Finally, summing (12) over the population of consumers yields the aggregate effect on the market share next period that is captured by the third term in (11).

Overall, increasing prices today will decrease demand tomorrow. Therefore, the prices predicted by this data generating process will be lower than the prices predicted under a static Nash-Bertrand oligopoly. A collusive industry may choose to *lower* prices even further, depending on the relative returns to increasing current prices and to increasing the future stock of addiction. Equation (13) defines the markups above marginal cost for all of the products in the market, given the structure of the industry defined by Ω_t.

$$p_t - mc_t = \Omega_t^{-1}\left[s(p_t) + \beta\left(p_{t+1}^{*} - mc_{t+1}\right)\Omega_t\right]. \tag{13}$$

To solve (13), we set p_{t+1}^{*} equal to its observed (equilibrium) value and solve for the p_t vector that clears the market.

Column 2 of Table 5 shows the predicted prices from the model of bounded rationality where firms play a two-period Nash-Bertrand pricing game. The predicted prices are approximately five to ten percent lower than the static Nash-Bertrand model, but they are still well above the observed prices in every year. Thus, we reject the hypothesis that firms were engaged in a two-period Nash-Bertrand pricing game after the MSA.

8.4. Pricing Behavior in a Dynamic Nash-Bertrand Oligopoly

Next we consider a more dynamic version of the model based on a looser notion of bounded rationality. As in the two-period model, firms are still assumed to make current pricing decisions using their perfect foresight of near-future equilibrium prices. The difference is that now firms are modeled as if they consider the full stream of discounted profits from all future periods.[41] Equation (14) is the first order condition that provides the basis for our price predictions in this long-term Nash-Bertrand pricing game.

$$s_j(p_t)+\sum_{r\in F_{f,t}}\left(p_{r,t}-mc_{r,t}\right)\frac{\partial s_{r,t}(p_t)}{\partial p_{j,t}}+\beta\sum_{r\in F_{f,t+1}}\left(p^*_{r,t+1}-mc_{r,t+1}\right)\frac{\partial s_{r,t+1}\left(p^*_{t+1}\right)}{\partial p_{j,t}}$$

$$+\frac{\beta^2}{1-\beta}\sum_{r\in F_{f,t+2}}\left(p^*_{r,t+2}-mc_{r,t+2}\right)\frac{\partial s_{r,t+2}\left(p^*_{t+2}\right)}{\partial p_{j,t}}=0\,. \tag{14}$$

In period t, firms know the equilibrium prices that will be charged in periods $t+1$ and $t+2$. They also recognize that their current pricing decisions will have ripple effects in periods 3 through T. However, they expect equilibrium returns to remain constant after period $t+2$. This approach depicts firms that are unable to predict exact market conditions far in advance but nonetheless recognize that their current pricing decisions may have long-term consequences. They predict these long-term consequences by extrapolating their expectations about near-future market conditions.

As in the static and two-period cases, we use the system of first order conditions to solve for the vector of current period prices that would maximize profits, given firms' expectations about the future and the structure of the market. Equation (15) expresses the system of first order conditions in matrix notation.

$$p_t-mc_t=\Omega_t^{-1}\left[s(p_t)+\beta\left(p^*_{t+1}-mc_{t+1}\right)\Omega_t+\frac{\beta^2}{1-\beta}\left(p^*_{t+2}-mc_{t+2}\right)\Omega_t\right]. \tag{15}$$

Column 3 of Table 5 reports the predicted prices. They are approximately ten to fifteen percent lower than our predictions for the two-period pricing rule but,

[41] See Tan (2006) for a dynamic oligopoly model of the cigarette industry that studies the effects of anti-smoking policies on the market structure. Firms are modeled as competing in price and advertising in a dynamic game. Tan (2004) develops a similar dynamic oligopoly model where firms are assumed to collude in price and compete in advertising.

again, they are still well above the observed prices for all years. While we reject the hypothesis that firms began a long-term Nash-Bertrand game after the MSA, the overall patterns of results in the first three columns of Table 5 are still suggestive of dynamic pricing behavior. As we move from the "static" model in Column 1 to the "dynamic" model in Column 3, point estimates for predicted prices move closer to the actual prices in our data. As a final step, we repeat the analysis in Columns 1-3 for a collusive industry.

TABLE 5: Comparison between Actual Prices and Predictions from Competing Models [a]

Year	Actual Price	Nash-Bertrand Oligopoly			Collusion		
		Static	2 period	dynamic	Static	2 period	dynamic
		(1)	(2)	(3)	(4)	(5)	(6)
1997	1.43	3.14 [2.74 3.84]	2.94 [2.76 3.53]	2.93 [2.76 3.49]	3.38 [2.88 4.41]	2.88 [2.74 3.48]	2.86 [2.72 3.39]
1998	1.65	3.25 [2.85 3.95]	3.04 [2.85 3.64]	2.96 [2.81 3.36]	3.49 [2.98 4.53]	2.99 [2.83 3.61]	2.78 [2.62 3.13]
1999	2.10	3.37 [2.98 4.09]	3.18 [2.99 3.80]	3.06 [2.93 3.31]	3.61 [3.12 4.65]	3.20 [3.04 3.87]	2.85 [2.25 3.24]
2000	2.36	3.46 [3.08 4.14]	3.29 [3.09 3.87]	3.08 [2.90 3.15]	3.70 [3.22 4.73]	3.21 [3.08 3.77]	2.65 [1.74 3.34]
2001	2.51	3.51 [3.13 4.18]	3.34 [3.14 3.92]	3.07 [2.86 3.20]	3.71 [3.25 4.69]	3.16 [3.07 3.65]	2.54 [1.60 3.37]
2002	2.66	3.55 [3.17 4.22]	3.40 [3.18 3.99]	3.19 [3.03 3.28]	3.74 [3.29 4.75]	3.27 [3.17 3.84]	2.67 [1.95 3.42]

[a] Bootstrapped 95% confidence intervals appear in square brackets underneath point estimates. Confidence intervals are based on 100 draws on the asymptotic distribution of the demand-parameter estimates from Column 5 of Table 4. Point estimates are medians calculated over the distribution of (pack,quarter) observations. Marginal costs are defined using the minimum price charged for each pack during the "Marlboro Friday" price war (1994-1996).

8.5. Did the MSA Lead Cigarette Firms to Collude?

To predict the prices that would be charged by a collusive industry under the static, two-period, and dynamic pricing rules, we simply repeat our analysis after setting all of the elements of the ownership matrix Ω_t^* equal to 1. The resulting price predictions will be equal to those for a cartel that maximizes profits by simultaneously setting the prices for every product (Bresnahan 1987; Nevo 2001). The results are reported in Columns 4-6 of Table 5.

Column 4 reports the prices that would be predicted for collusive firms engaged in a static pricing rule. As we would expect, prices are higher than in the static Nash-Bertrand game (Column 1). Results from the two-period model are reported in Column 5. Clearly, predicted prices are still too high for the model to rationalize observed behavior. For example, we predict that the median price in 2002 would lie in the interval [3.17,3.84], while the observed price is 2.66. Therefore, we reject the (joint) hypothesis that firms collude using a two-period pricing rule.

A comparison between Column 2 and Column 5 reveals one of the interesting implications of collusion on prices for a habit-forming good. Notice that our point estimates for prices in Column 5 are lower than in Column 2. This is because a collusive industry is able to internalize the effect of higher prices on addiction. By collectively dropping their prices, all firms can benefit from the increased stock of addiction in the future.

Finally, when we model the cigarette industry as being collusive with a dynamic pricing strategy, our point estimates for predicted prices appear to converge to the prices that were actually charged after the MSA. The predicted prices in Column 6 are far above actual prices from 1997 through 1999. Beginning in 2000, our confidence intervals on predicted prices include actual prices. By 2002, our point estimate for the predicted median price ($2.67) is nearly the same as the actual median price ($2.66). Thus, the results in Table 5 fail to reject the hypothesis that the major cigarette firms are forward-looking in their pricing decisions and began to set prices in concert after the MSA.

8.6. Robustness Check: Predicted Equilibrium Prices based on Accounting Costs

Our rejection of competitive pricing strategy is based on the assumption that marginal costs are revealed by the lowest prices we observe between 1994 and 1996. If instead, firms set prices above marginal cost throughout the Marlboro Friday price war, our predictions in the first three columns of Table 5 will tend to overstate the prices that would be charged by a competitive oligopoly. To assess the sensitivity of our results to the marginal cost assumption we develop an alternative set of predictions for equilibrium prices based on firm-specific accounting costs assembled by Bulow and Klemperer (1998). Since their accounting figures exclude the opportunity cost of the firms' resources, they should provide lower bounds on the true marginal cost and lead to predictions for equilibrium prices that are also lower bounds.

Table 6 reports the prices we predict for the three oligopoly models under the accounting-cost scenario. The pack-weighted average accounting cost (54 cents/pack) is approximately half the size of our baseline estimate for marginal cost (95 cents/pack). Despite the wide gap between the two measures, we continue to systematically reject the static and two-period models of Nash-Bertrand pricing. The key difference between Tables 5 and 6 is that, under the accounting-cost scenario, we can no longer reject the model of long-term oligopoly pricing for 2000-2002. During those three years, the point estimates in Column 3 of Table 6 are nearly the same as actual prices, which are nearly the same as our predictions for the model of long-term collusion under our baseline estimates for marginal cost.

TABLE 6. Actual Prices and Predictions Based on Accounting Cost [a]

Year	Actual Price	Nash-Bertrand Oligopoly		
		Static	2 period	dynamic
		(1)	(2)	(3)
1997	1.43	2.78 [2.37 3.51]	2.62 [2.40 3.21]	2.46 [2.34 2.65]
1998	1.65	2.89 [2.47 3.63]	2.72 [2.49 3.31]	2.45 [2.26 2.57]
1999	2.10	3.02 [2.60 3.77]	2.85 [2.63 3.45]	2.59 [2.36 2.70]
2000	2.36	3.08 [2.68 3.79]	2.96 [2.71 3.55]	2.52 [1.99 2.76]
2001	2.51	3.11 [2.72 3.80]	3.00 [2.74 3.60]	2.52 [1.86 2.80]
2002	2.66	3.14 [2.76 3.84]	3.05 [2.78 3.65]	2.67 [2.25 2.86]

[a] Bootstrapped 95% confidence intervals appear in square brackets underneath point estimates. Confidence intervals are based on 100 draws on the asymptotic distribution of the demand-parameter estimates from Column 5 of Table 4. Point estimates are medians calculated over the distribution of (pack,quarter) observations. Marginal costs are defined using the firm-specific measures of accounting cost assembled by Bulow and Klemperer (1998).

If we view the minimum prices that were charged during the price war as upper bounds on the true marginal cost, and accounting costs as lower bounds, then our results would imply that cigarette manufacturers are engaging in a dynamic pricing strategy that falls somewhere between collusion and Nash-Bertrand competition. This is a cautious interpretation. We suspect that our baseline estimates for marginal costs are closer to the truth than the accounting figures. It is hard to reconcile the large (nearly 100%) difference between accounting costs and the minimum prices that were changed during the Marlboro Friday price war. The size of this difference leaves us more inclined to reject the notion of competitive pricing.

Regardless of which estimates we use for marginal cost, two implications are clear. First, the Master Settlement Agreement signaled a change in the nature of competition within the cigarette industry. None of our models of oligopoly or collusive pricing are capable of explaining prices prior to the Agreement. Second, we systematically reject the static and two-period models of Nash-Bertrand pricing after the MSA. Actual prices are more consistent with dynamic pricing strategies that account for the long-term consequences of current pricing decisions.

9. Conclusions

This paper has documented a change in the nature of competition within the cigarette industry that coincided with the 1997 Master Settlement Agreement. Prior to the agreement, we observe firms setting prices on the inelastic region of pack-level demand curves for consumers in Knoxville, TN. This is consistent with coverage of the famous “Marlboro Friday” price war. After the agreement, cigarette manufacturers changed their pricing behavior, setting prices on a more elastic region of their demand curves. Overall, our results support the hypothesis that the Master Settlement Agreement acted as a coordinating device for firms to collectively end their price war and raise cigarette prices. These results are certainly suggestive, but we must also be cautious in using data from a single metropolitan area to draw conclusions about pricing strategy throughout the rest of the nation. Further investigation of data from other markets is warranted.

In addition to documenting a change in competition within the cigarette industry, our analysis has some novel features which may apply elsewhere. For example, state governments have been unpleasantly surprised by the extent to which the volume adjustment has decreased their MSA payments (Council of State Governments, 2002). We provided the first formal illustration of how the volume adjustment to the Master Settlement Agreement transforms the lump-sum payments into a per-unit tax. With information on the state-level demand for cigarettes, our analysis could be extended to calculate the state tax rate that would maximize the combined revenue from taxes and MSA payments.

Finally, from a modeling perspective, our work represents a first pass at developing a discrete-choice model of the demand for cigarettes that explicitly acknowledges consumers are addicted to the product and forward-looking. There are at least two important issues to consider for further research. The first is moving closer to a fully dynamic model of rational addiction. Our model captures the effect of addiction on the current decision for whether to smoke, as well as the effect of smokers’ expectations for whether prices will increase in the near future. The main difference between this behavioral model and that of Becker and Murphy (1988) is that we have not modeled the potential connection between smokers’ current choices and their recognition that their future consumption will depend on their current consumption decisions. Identifying this effect in the context of our discrete-choice model would require micro-level panel data on consumer purchases.

With access to micro panel data, one could also extend our work to develop a fully dynamic estimable model of brand choice, heterogeneity in smoking intensity, and the choice to purchase chemical quitting aids that reduce nicotine cravings. A model with these features would be capable of reproducing the "cycle of addiction" predicted by Gul and Pesendorfer (2007). A possible starting point for this important line of research would be to build addiction into the structure of dynamic choice models such as Hendel and Nevo (2006) and Gowrisankaran and Rysman (2009).

10. References

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