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PRICE UNCERTAINTY, TAX POLICY, AND ADDICTION: EVIDENCE AND IMPLICATIONS

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ABSTRACT

Consumption of addictive goods is subject to habit formation. Forward-looking individuals must, therefore, be concerned about future prices when making current consumption decisions. We study prices for tobacco products based on a unique data set provided by the Bureau of Labor Statistics. Our empirical findings suggest that prices have been highly volatile during the past decade. Price uncertainty has a potentially large impact on the economic well-being of young individuals with relatively low levels of disposable income. We develop a model to study consumption of addictive substances under price uncertainty. Our results indicate that optimal decision rules of low income individuals can crucially depend on subjective beliefs about future prices and the length of the planning horizon. These results imply that tax policies are most effective in reducing teenage cigarette consumption if they credibly alter individuals' beliefs about future prices.

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1 Introduction

One of the main objectives of recent health policy has been to reduce cigarette consumption of teenagers. Improving our understanding of the behavior of younger individuals is essential for the effective design of public policies. Reducing cigarette consumption of teenagers is challenging because teenagers are likely to experiment with tobacco products despite the known harmful effects of these goods (Becker and Murphy, 1988). Experimentation with cigarettes that begins with temptation (Orphanides and Zervos, 1995) and lack of self-control (Gul and Pessendorfer, 2001) leads to addiction. Peer pressure and clever marketing campaigns may be hard to resist. Individual consumption plans may not be time consistent (Gruber and Koeszegi, 2001) or are subject to systematic mistakes (Bernheim and Rangel, 2002).

Since cigarette consumption is subject to habit formation and addiction, forward-looking individuals must be concerned about future prices when making current consumption decisions. Thus current cigarette consumption of individuals depends not only on preferences, but also on beliefs that individuals hold about the evolution of future prices. Given this fundamental property of addiction models, it is surprising that almost all previous research on smoking and addiction has made little effort to model individual beliefs about future tax and price policies. Instead research has typically relied on the assumption that individuals have perfect foresight.[1] The lack

[1] The most frequently used test of the rational addiction model which is based on the comovement

of incorporating realistic price expectations into the analysis of addictive goods would be understandable if prices were stable and easy to predict. However, we show in this paper that exactly the opposite is the case.

To get a better understanding of price volatility in the market of tobacco products, we follow a dual approach. First, we discuss the main changes in the market structure, tax policies, and the regulatory environment. The upshot of this discussion is that there have been a large number of policy and regime changes in the market for tobacco products in the past decade. Changes in market structure, taxes, and regulatory policy often lead to large changes in prices of tobacco products. It is hard to believe that young adults perfectly anticipated most of these changes as typically assumed in the literature.

We then formalize the analysis and study the empirical properties of prices of tobacco products. We use a unique data set to assess the importance of volatility in prices of tobacco products. The data are provided by the Bureau of Labor Statistics. The main advantages of this data set are twofold. First, we can analyze prices on the metropolitan area level. Our analysis thus avoids aggregation bias inherent in data at the state or federal level. Second, prices are sampled on a monthly basis, which allows us to focus on price variation within short time periods.

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of current consumption with lagged, current, and future prices implicitly assumes that individuals have perfect foresight. See, for example, Chaloupka (1991), Becker, Grossman, and Murphy (1991, 1994), and Chaloupka and Warner (2000).

To capture the main stochastic properties of the data, we estimate regime switching models proposed by Hamilton (1989, 1990). Our empirical findings suggest that there is a tremendous variation in prices of tobacco products among the set of metropolitan areas analyzed in this study. Furthermore, estimates based on aggregate time series often underestimate the amount of price volatility experienced on the local level. For the majority of metropolitan areas studied in this paper, there seem to be two distinctly different regimes of price changes. There are time periods which are fairly stable and exhibit only small changes in tobacco prices. These periods are often followed by short periods which are much more volatile and exhibit large swings in prices. In these periods, predicted confidence intervals for future prices are quite large.

Given our estimates of price uncertainty, we then investigate how cigarette consumption of forward-looking individuals depends on expectations about future prices. We extend the basic addiction model to analyze the impact of individual beliefs about future tax and price policies on consumption of addictive substances. We solve the model under a variety of behavioral hypotheses ranging from myopic to forward looking behavior with correct price expectations. Our computational experiments show that consumption plans of forward-looking individuals can be quite sensitive to beliefs about future taxes and prices.

These results have important policy implications. Tax policies are only effective if they permanently change the beliefs that individuals hold about future prices. If a tax increase is perceived to be temporary, it will have, at best, modest effects on individual consumption. A tax policy which would allow the government to commit to significant tax increases in the future would have strong immediate effects on consumption. Empirical studies which fail to distinguish between transitory and permanent tax and price changes and ignore uncertainty of future outcomes are likely to yield biased estimates of the underlying parameters of the behavioral model.[2]

The rest of the paper is organized as follows. Section 2 provides a brief overview of the industry and discusses the empirical evidence on price volatility of tobacco products. This part of the analysis is based on a unique data set of monthly prices collected by the Bureau of Labor Statistics (BLS). Section 3 discusses estimation of pricing models. Section 4 presents our estimation results. In section 5 we provide a rigorous theoretical and computational analysis of the policy implication of price uncertainty. Section 6 offers some conclusions that can be drawn from the analysis.

2 Empirical Evidence

Prices of tobacco products are largely determined by the underlying market structure. The U.S. tobacco industry has been highly concentrated for several decades. At

[2] This point, which is largely ignored in the addiction literature, is well documented in the empirical literature of charitable donations. See, for example, Randolph (1995) and Auten, Sieg, and Clotfelter (2002).

the beginning of 1988, six firms produced virtually all domestic cigarettes: Philip Morris (PM), R.J. Reynolds (RJR), Brown & Williamson (B&W), American Tobacco, Lorillard, and the Liggett Group. After B&W merged with American Tobacco in 1995, market shares were as follows: PM 46 percent, RJR 26 percent, B&W (including American) 18 percent, Lorillard 8 percent, and Liggett 2 percent.[3]

The best-selling American brand is Marlboro which has retained the largest market share for a single brand (35 percent in 1997) throughout the past two decades, although this has been challenged by the rise of generic, discount cigarettes. Cigarette manufacturers sell a number of different brands at different prices. Products were not significantly differentiated by price until the late 1970s, when the first discount and generic brands were introduced. Such brands constituted just 1 percent of the market in 1981, but as manufacturers ratcheted up prices at a steady 10 percent, individuals eventually began to switch brands. Generics grew to 9 percent of the market in 1986 and exploded thereafter, peaking around 37 percent of the market.

Manufacturers who had reaped huge profits from premium brands, such as Marlboro or Camel, quickly found that they were now competing both with themselves and with one another. All manufacturers briskly sold discount brands while trying to preserve their traditional brands. Philip Morris stopped the trend temporarily in April 1993 by slashing the price of its flagship Marlboro brand and a price war fol-

[3]Most of the statistics reported are taken from S&P industry reports published during the 1990's.

lowed. Premium brands sold at a 40 percent discount through autumn, when prices were finally raised by Philip Morris, a move immediately followed by the rest of the oligopoly. At the time of the price cut, profit margins on premium brands were about 55 cents per pack; discount brands, on the other hand, provided only a five-cent profit.

In this study, we provide a comprehensive empirical analysis of the properties of cigarette prices. Our data come from the Price Indexes for Tobacco and Smoking Products collected by the Bureau of Labor Statistics (BLS). Our data set consists of monthly price series for a number of metropolitan areas in the U.S. covering the time period from 1988 to 2000.[4] The main advantages of this data set are two fold. First, it allows us to analyze prices on a disaggregate level. Our analysis thus avoids aggregation bias in the analysis. Second, prices are sampled on a monthly basis, which allows us to focus on price variation within shorter periods. Empirical analysis based on quarterly or yearly data is likely to underestimate the significant amount of price variation in the underlying price processes.

The BLS sample contains price indexes for a large number of metropolitan areas in the U.S. We focus on the following five metropolitan areas: New York City, Cleveland, Miami, Los Angeles, and Denver. This subsample is chosen to reflect the geographical diversity within the United States. To avoid problems due to differences in state

[4]Past research has primarily relied on either the Tobacco Institute's weighted average price by state or data collected by ACCRA. To our knowledge Sloan, Smith, and Taylor (2002) is the first study which has used the BLS data in empirical analysis. A careful discussion of different price data and the advantages of the BLS data is also given in Chapter 8 of Sloan et al. (2002).

taxes, we selected metropolitan areas which are primarily contained in one state. For comparison purposes we also analyze an aggregate time series for the complete United States.

For our empirical analysis, we constructed two separate time series for each of the six subsamples. The unadjusted prices are based on the the raw data. We also compute an adjusted price series by removing two outliers. In our data set prices of tobacco products increased approximately 16 percent on average between November and December 1998 following the settlement between the tobacco industry and the states which were suing to recover medical expenditures. While this price increase may be a salient feature of the data, it is also desirable to analyze the data without this outlier. We therefore construct an adjusted price series which eliminates this large price increase. Another large price change occurred between August and September 1993, when prices dropped on average by 6 percent. This price change is largely driven by the inclusion of discount cigarettes into the index. Since this is a technical correction of the index, we also exclude it from our adjusted price series.

Table 1 reports descriptive statistics of our six sub-samples. It reports means, standard deviations, minimums and maximums for price levels. The reported minimum typically occurred during the beginning of the time period, the maximum towards the end. We, therefore, find that price increased on average by approximately 100 percent during the observation period.

Table 1: Descriptive Statistics

	Price Levels					
	Mean	SD	Min	Max	T-I	T-II
			Unadjusted Prices			
U.S.	125.06	22.77	100.00	190.91	0.03	-0.46
N.Y.	120.85	14.92	100.00	167.35	0.22	1.60
Cleveland	128.29	19.92	99.43	196.70	0.00	-11.69
Miami	99.17	14.49	84.99	146.40	0.02	0.08
L.A.	115.76	24.54	96.48	191.53	0.05	-1.34
Denver	113.90	16.10	89.60	159.98	0.06	-6.79
			Adjusted Prices			
U.S.	130.38	16.99	100.00	168.08	0.00	-14.11
N.Y.	125.46	14.71	100.00	166.87	0.07	-0.63
Cleveland	131.56	16.13	99.43	177.89	0.00	-35.27
Miami	100.85	7.74	91.67	127.94	0.03	-3.72
L.A.	125.81	12.27	98.86	152.53	0.00	-26.85
Denver	116.24	8.17	99.22	137.70	0.00	-33.69

INSERT FIGURE 1 HERE

To illustrate the basic properties of our data, we also provide plots of the six different time series analyzed in this paper in Figure 1. Adjusted and unadjusted price levels are given by solid lines and dots, respectively. Figure 1 suggests that prices of tobacco products increased substantially throughout the time period in the United States and in the five metropolitan areas analyzed in this paper. However, there are also time periods in the sample in which prices of tobacco products decreased. A comparison of the five metropolitan areas shows that there is significant heterogeneity in prices among geographic entities in the United States. As discussed below, some of these price differences are due to differences in taxation among states. Not surprisingly, we also find that prices in metropolitan areas are more volatile than those in the US aggregate.

Table 1 also reports two stationarity tests, denoted by T-I and T-II. Following Hamilton (1994) we consider the following baseline model to test for stationarity:

$$p_t \; = \; a \, + \, b \, p_{t-1} \, + \, c \, t \, + \, e_t \tag{2.1}$$

where p_t denotes price levels at time t and e_t is a white noise error term. Our first test statistic, T-I, gives the p-values for the null $c = 0$ (assuming $|b| < 1$). Hence small p-values are evidence in support of a nonstationary model because of the time trend.

T-II is the test statistic – not the p-value – for the null b=1 and c = 0.[5] Approximate 5 percent and 1 percent critical values for this test statistic are 6.48 and 8.72.

The results of the stationarity tests suggest that prices in levels may not be stationary. The p-values for the first test statistic are very low, the second test statistic is often above the critical levels at commonly used significance levels. We therefore difference the data and run the same tests on the differenced data. Our results suggest that first differencing the data yields stationary time series, especially once we also account for the two outliers discussed above. We therefore conclude that it is reasonable to model prices in first differences as a stationary time series. To illustrate the main properties of the data in first differences, we plot these time series in Figure 2. We do not include unadjusted price differences because the only difference between this and adjusted is at the two correction points.

INSERT FIGURE 2 HERE

Figure 2 suggests that there are time periods which are characterized by large volatilities in prices. The last few years in our sample are very good examples for these high volatility time periods. At the same time there appear to be periods which have a fairly low variation in prices. For example, price changes are much smaller in the middle of our observation period.

[5]See p. 497-502 of Hamilton (1994) and refer to the table on p. 764, case 4.

Some of the price variation observed in our sample is a direct result of changes in state and federal tax policies which were implemented during the past decade. In 1983, the federal excise tax was doubled from \$0.08 per pack to \$0.16 per pack. This rate held for a decade, when the federal rate was increased another \$0.08 to \$0.24 per pack. In 1997, legislation passed increasing the federal tax on cigarettes to \$0.34 per pack in 2000 and \$0.39 per pack in 2002.

A larger part of the cross-sectional variation of prices of tobacco products is due to differences in state tax policies.[6] Table 2 summarizes the main features of federal and state tax policies during the last decade.[7] We focus on the five states which contain the metropolitan areas of our study. We find that state taxes ranged from 18 to 35 cents per pack in the beginning of the decade. At the end of the decade the differences were even larger. Tax rates changed up to two times on the state level.

Table 2: Annual Cigarette Taxes (in cents per package)

	Federal	State				
		New York	Ohio	Florida	California	Colorado
Beginning	16	39	18	34	35	20
End	24	56	24	34	87	20
SD	3	8	3	0	16	0
# of Changes	2	1	1	0	2	0

[6]Taxes on tobacco products have long been a source of significant revenue for state and local governments. Cigarettes account for the bulk of tax revenue, due to consumption habits and the structure of tobacco tax rates. Although aggregate cigarette consumption peaked in 1981, revenue from cigarette taxes has increased substantially since then.

[7]The statistics reported in Table 2 are based on Orzechowski and Walker (2001).

Cigarette prices have also been affected by various different lawsuits filed against the major tobacco companies. Most important, individual states sued to recoup tobacco-related Medicaid payments. In 1996, the Liggett Group broke ranks with other manufacturers by reaching a settlement that assumed some liability for five states' medical expenses and settled a class-action lawsuit. Although Liggett's penalty was not particularly large, this lawsuit was symbolic because tobacco companies had previously defended themselves at any costs against legal challenges and won. During the lawsuits, thousands of documents were subpoenaed, revealing that tobacco companies had deliberately tailored cigarettes to make them more addictive. All manufacturers eventually caved in. By 1998, Texas, Florida, Mississippi, and Minnesota reached settlements totaling $40 billion, to be paid over 25 years.

The most important settlement to date was reached in November 1998. The Master Settlement Agreement (MSA) with 46 states totaled $206 billion for Medicaid expense to be paid over 25 years. Also included were significant restrictions on advertising and promotions, and a portion of the settlement funds were earmarked for prevention of tobacco consumption. The MSA was defeated in Congress. The defeated proposition would have put even stronger restrictions on cigarette marketing and sales.

We have thus seen that prices of cigarettes are largely influenced by changes in the market structure, changes in tax policies and changes in the regulatory environment.

The last decade experienced many changes which caused prices of tobacco products to be especially volatile. To get additional insights into the properties of cigarette prices, we provide a more rigorous empirical analysis.

3 Estimation

We estimate time series models to capture the main empirical regulations in the data. The starting point of our analysis are regime switching models pioneered by Hamilton (1989, 1990). We consider a first-order autoregressive regime switching model which can be written as:

$$\Delta p_t \;=\; \mu_{s_t} \;+\; \rho_{s_t}\, \Delta p_{t-1} \;+\; \epsilon_{s_t} \tag{3.1}$$

where s_t is the (unobserved) state of the time series process at time t. In a regime switching model the parameters of the autoregressive process, μ_{s_t} and ρ_{s_t}, and the distribution of the error terms depend on the state of the process. This feature of the model allows us to capture the fact that prices are stable in some periods and and highly volatile in other periods. We assume that ϵ_{s_t} is i.i.d. $N(0, \sigma_s^2)$. For notational simplicity, let us write the density of Δp_t conditional on $s_t = j$ and Δp_{t-1} as

$$f(\Delta p_t \,|s_t = j, \Delta p_{t-1}; \theta) \tag{3.2}$$

where θ is the parameter vector to be estimated.

The evolution of the state of the process is modelled as the outcome of an unobserved J-state Markov chain. For simplicity let us consider a two-regime model ($J = 2$). The Markov transition matrix for a two-regime model is given by:

$$Q = \begin{bmatrix} q_{11} & q_{21} \\ q_{12} & q_{22} \end{bmatrix} \tag{3.3}$$

Denote the history of price changes up to time t-1 as $\Delta\vec{p}_{t-1}$. The probability that the process is in state $s_t = j$ conditional on $\Delta\vec{p}_{t-1}$ is written as $Pr\{s_t = j \mid \Delta\vec{p}_{t-1}; \theta\}$. Given that we observe a realization Δp_t, we draw inference about the state of process by iterating the following two equations:

$$Pr\{s_t = i \mid \Delta\vec{p}_t; \theta\} = \frac{f(\Delta p_t \mid s_t = i, \Delta p_{t-1}; \theta)\ Pr\{s_t = i \mid \Delta\vec{p}_{t-1}; \theta\}}{\sum_{j=1}^{2} f(\Delta p_t \mid s_t = j, \Delta p_{t-1}; \theta)\ Pr\{s_t = j \mid \Delta\vec{p}_{t-1}; \theta\}} \tag{3.4}$$

and

$$\begin{bmatrix} Pr\{s_{t+1} = 1 \mid \Delta\vec{p}_t; \theta\} \\ Pr\{s_{t+1} = 2 \mid \Delta\vec{p}_t; \theta\} \end{bmatrix} = \begin{bmatrix} q_{11} & q_{21} \\ q_{12} & q_{22} \end{bmatrix} \begin{bmatrix} Pr\{s_t = 1 \mid \Delta\vec{p}_t; \theta\} \\ Pr\{s_t = 2 \mid \Delta\vec{p}_t; \theta\} \end{bmatrix} \tag{3.5}$$

Equations (3.4) and (3.5) completely characterize the stochastic evolution of the state of the process.

Suppose we have a sample of price changes observed over a sequence of T periods. The results above imply that the likelihood function of the data is given by the following equation:

$$L = \prod_{t=1}^{T} \sum_{j=1}^{J} Pr\{s_t = j \mid \Delta\vec{p}_{t-1}; \theta\} \; f(\Delta p_t \mid s_t = j, \Delta p_{t-1}; \theta) \tag{3.6}$$

The likelihood function does not have a closed-form analytical solution, but needs to be computed using an EM algorithm. In the EM algorithm, we start with an initial guess for the probabilities of each state and then iterate forward using equations (3.4) and (3.5) to compute the conditional probabilities characterizing each state at time t.

Before we report the estimation results, we offer two additional observations. First, we can relax the AR(1) assumption and allow for more complicated lag-structures in equation (3.1). Second, we can also allow for more than two states in the underlying process of prices. However, the two-state first-order autoregressive regime switching model is appealing in our application, as discussed in detail in the next section.

4 Estimation Results

We estimate the regime switching models using the adjusted and unadjusted data from 5 different cities and an aggregate series for the U.S. Table 2 reports the point estimates of the parameters of the different regime switching models. Estimated standard errors are reported in parenthesis.

Table 2 reinforces our findings that there is substantial heterogeneity among the metropolitan areas in our data set. The parameter estimates differ substantially among the six samples, in particular when using the unadjusted price data. The estimates for the means are typically positive in both regimes. They are often significantly different from zero. This result reflects the earlier observation that prices were mostly increasing during the observation period. Using the adjusted data, we find that the point estimates for ρ_s are often negative in both regimes. This result suggests that there is some mean reversion in the data. A period of positive price changes is likely to be followed by a period with negative price changes. The point estimates of the variances suggest that price series of metropolitan areas are more volatile than the aggregate U.S. time series. This result is not surprising. Aggregate data are likely to underestimate the amount of price volatility faced by most individuals.

Table 2 also contains the p-value for the null-hypothesis that the two regimes are the same. We have argued before that regime switching allows us to differentiate between low and high volatility periods in the sample.[8] Table 2 shows that two-state regime switching models fit the data better than simple AR(1) specifications,

[8]The p-values and standard errors were calculated by 1000 bootstrap replications. To ensure that the estimates for each replication were obtained from a global optimum, we started the EM from several different initial values, and found that this simple model was rather robust to different starting values.

Table 3: Markov-Switching Estimates

	q_{11}	q_{22}	μ_1	μ_2	ρ_1	ρ_2	σ_1^2	σ_2^2	p-value
				Unadjusted Prices					
U.S.	0.911	0.972	1.909	0.437	0.013	0.112	45.980	0.499	0.088
	(0.105)	(0.028)	(2.167)	(0.101)	(0.495)	(0.072)	(29.410)	(0.007)	
N.Y.	0.225	0.563	1.752	0.259	-0.602	-0.018	11.012	0.216	0.103
	(0.106)	(0.102)	(0.714)	(0.086)	(0.514)	(0.03)	(2.877)	(0.309)	
Cleveland	0.824	0.911	1.661	0.789	-0.451	-0.266	80.365	2.638	0.337
	(0.122)	(0.052)	(1.832)	(0.225)	(0.244)	(0.094)	(22.163)	(1.025)	
Miami	1.000	0.000	0.435	0.000	0.007	0.000	12.554	0.000	1.000
	(0.000)	(0.000)	(0.354)	(0.000)	(0.082)	(0.000)	(5.479)	(0.000)	
L.A.	0.418	0.922	6.807	0.537	1.158	-0.268	95.471	5.177	0.292
	(0.191)	(0.059)	(5.84)	(0.274)	(1.39)	(0.056)	(81.317)	(1.306)	
Denver	0.604	0.546	1.084	-0.006	-0.125	-0.018	55.654	0.306	0.429
	(0.104)	(0.101)	(1.159)	(0.148)	(0.192)	(0.029)	(12.634)	(2.314)	
				Adjusted Prices					
U.S.	1.000	0.000	0.818	0.000	-0.325	0.000	3.714	0.000	1.000
	(0.000)	(0.000)	(0.250)	(0.000)	(0.164)	(0.000)	(1.232)	(0.000)	
N.Y.	0.165	0.599	1.723	0.267	-0.599	-0.019	9.969	0.215	0.142
	(0.102)	(0.100)	(0.775)	(0.079)	(0.644)	(0.030)	(2.783)	(0.256)	
Cleveland	0.775	0.904	1.218	0.680	-0.551	-0.259	69.399	2.528	0.470
	(0.153)	(0.048)	(1.910)	(0.215)	(0.480)	(0.089)	(20.840)	(0.854)	
Miami	1.000	0.000	0.289	0.000	-0.096	0.000	6.856	0.000	1.000
	(0.000)	(0.000)	(0.252)	(0.000)	(0.097)	(0.000)	(2.176)	(0.000)	
L.A.	0.911	0.949	0.757	0.387	-0.462	0.024	19.453	1.892	0.508
	(0.160)	(0.053)	(1.308)	(0.202)	(0.335)	(0.136)	(6.145)	(0.623)	
Denver	0.564	0.583	0.448	0.055	-0.378	-0.023	44.169	0.486	0.502
	(0.117)	(0.099)	(1.135)	(0.143)	(0.216)	(0.036)	(10.342)	(1.348)	

at least for the majority of the disaggregate time series. The point estimates suggest that regime 1 is characterized by large changes in prices accompanied with large volatility. These are the periods of price wars or those characterizing changes in tax or regulatory policies. Regime 2, in contrast, is fairly stable and shows only modest amounts of volatility and price changes. While most of the parameters are estimated with relatively large standard errors, we find that the parameters are typically jointly significantly different from zero.[9]

INSERT FIGURE 3 HERE

One of our main interests is to characterize the amount of price uncertainty faced by individuals. To illustrate our main results, we perform a number of Monte Carlo experiments. Using the estimates from the unadjusted data, we simulate 10,000 price realizations for three of the six models for up to 5 years. The solid line ($-$) in Figure 3 shows the predicted mean prices for 60 months for Cleveland. The dashed lines ($- \; -$) show the predicted means plus (minus) two estimated standard deviations. Figure 3 illustrates that price forecasts are subject to large standard errors. Not surprisingly, the estimated standard error increases with the length of the forecasting

[9] We also estimated AR models with more than one lag and found that the AR(1) specification is sufficient to capture the main regularities in the data. We have no a priori reasons to believe that a two state regime switching model will fit the data the best. Determining the number of states in the model is, however, complicated because standard regularity assumptions imposed in likelihood ratio tests are not met (Hansen, 1992). We performed a number of sensitivity tests to investigate whether adding an additional state to our model would change the main empirical results. All of tests suggested that adding a third regime the model does not improve the fit of the model.

interval. But price forecasts for even short periods are not very accurate given the variance estimates in the two regimes of the Markov switching model.

Forward-looking individuals must be concerned about the potential of large price increases. To illustrate these risks, we compute the probability that prices will increase by 5 (10, 25 or 50) percent over a 1 (2, 3, 4 or 5) year period. Table 4 reiterates our findings that forward-looking individuals must expect that prices are going up, no matter where they live. The main differences are that prices in New York are predicted to increase by smaller amounts than prices in Cleveland or Los Angeles. We find that young individuals face significant price risks. Consider, for example, the LA metropolitan area. The probability that prices will increase by at least 10 (25 or 50) percent in the first year alone is 0.31 (0.12 and 0.04). That probability increases to 0.93 (0.74 and 0.42) if one considers a five year interval. While, the estimated probabilities are of a smaller magnitude for Cleveland and New York, individuals face substantial risks of large price increases in each metropolitan area.

In summary, prices for tobacco products have increased during the observation period. Moreover, prices are also highly volatile. Our findings imply that future prices are extremely hard to predict accurately. Since their disposable income is low, teenagers are most likely to be affected by large price increases. Consider, for example, a 12 year old teenager that smokes 10 cigarettes (half a pack) per day. His or her monthly consumption is approximately 15 packs of cigarettes. Using a conservative

Table 4: Probability of Price Increases

	New York			
	at least 5 percent	at least 10 percent	at least 25 percent	at least 50 percent
1 year	0.480	0.096	0.000	0.000
2 years	0.813	0.482	0.005	0.000
3 years	0.925	0.757	0.067	0.000
4 years	0.974	0.893	0.242	0.000
5 years	0.990	0.954	0.476	0.002
	Cleveland			
	at least 5 percent	at least 10 percent	at least 25 percent	at least 50 percent
1 year	0.444	0.187	0.010	0.000
2 years	0.706	0.460	0.066	0.000
3 years	0.814	0.653	0.178	0.004
4 years	0.870	0.769	0.322	0.019
5 years	0.913	0.838	0.461	0.049
	Los Angeles			
	at least 5 percent	at least 10 percent	at least 25 percent	at least 50 percent
1 year	0.534	0.309	0.118	0.039
2 years	0.782	0.610	0.282	0.107
3 years	0.888	0.789	0.458	0.195
4 years	0.933	0.878	0.616	0.302
5 years	0.956	0.927	0.739	0.419

price of \$3, the individual's monthly expenditure on cigarettes is \$45 dollars in the first year. If s/he lives in the LA area, the teenager would expect to pay an additional 11 percent on average, or \$5.1, to purchase the same quantity one year later. However, there is a probability of 0.04 that s/he would have to spend at least another \$22.5 to purchase 15 packs a month. Disposable income for teenagers is likely to be small. If most young individuals are severely cash constrained, we would expect that these individuals would take, at least, some of these risks into consideration when making their decisions. We consider these issues more rigorously in the next section.

5 Price Uncertainty, Tax Policy, and Addiction

The empirical evidence suggests that individuals face uncertainty about future prices of cigarettes. The next step of our analysis is to extend the basic Becker and Murphy (1988) model to account for beliefs that individuals hold about future prices. We would like to know whether price uncertainty and subjective beliefs about future prices and tax rates can have substantial effects on the consumption of addictive goods such as cigarettes.

Let us consider an individual who can consume two types of goods: a non-addictive good denoted c_t and an addictive good a_t. The stock of addictive consumption, S_t, evolves according to the following law of motion:

$$S_{t+1} \;=\; \delta\, S_t \;+\; a_t \tag{5.1}$$

where δ is the rate of depreciation of the addictive stock. Individuals rank alternatives according to a utility function:

$$U_t \;=\; u(c_t,\; a_t,\; S_t) \tag{5.2}$$

which satisfies all the standard regularity assumptions imposed in the addiction literature.[10] Individuals may or may not be forward-looking. We assume that the relevant planing horizon of an individual is T periods. Individuals maximize expected intertemporal utility:

$$E\left(\sum_{t=1}^{T} \beta^{t-1}\, u(c_t,\; a_t,\; S_t)\right) \tag{5.3}$$

where β is the discount factor.[11] Thus if $T = 1$, individuals are myopic. If $T = \infty$ individuals are perfectly forward looking. Individuals face a sequence of budget

[10] These assumptions are smoothness, concavity, complementarity of a and S, and non-negativity.

[11] Alternatively, one could assume that individuals engage in hyperbolic discounting as suggested by Harris and Laibson (2001) and Gruber and Koeszegi (2001). Our main argument rests on the notion that individuals are forward-looking to a certain degree. Whether individuals adopt time-consistent or inconsistent plans is not important for our analysis.

constraints given by:

$$c_t \; + \; p_t \, a_t \;\; = \;\; y_t \tag{5.4}$$

p_t is the gross-of-tax price of the addictive good at time t. y_t denotes income at time t.[12] Prices evolve according to a stochastic law of motion. Individuals have subjective beliefs regarding the law of motion of prices. Price expectations are characterized by the transition density, $f(p_{t+1} \, | p_t)$.

Since we abstract from the saving decision, we can simplify the decision problem of the individuals and substitute the budget constraint into the utility function. Define

$$w(y_t, p_t, a_t, S_t) \;\; = \;\; u(y_t \; - \; p_t a_t, \; a_t, \; S_t) \tag{5.5}$$

Further, substituting the law of motion of the addictive stock into the value function, we can express the dynamic programming problem faced by a forward-looking individual as follows:

$$\begin{aligned} V_t(y_t, S_t, p_t) \;\; = \;\; & \max_{a_t \in [0, y_t/p_t]} \; w(y_t, p_t, a_t, S_t) \\ & + \beta \int V_{t+1}(y_{t+1}, a_t + \delta S_t, p_{t+1}) \; f(p_{t+1} | p_t) \; dp_{t+1} \end{aligned} \tag{5.6}$$

[12]For computational simplicity, we assume that there is no savings. This is a reasonable assumption for young individuals.

Solving the model, optimal decisions of individuals can be characterized by a policy function written as: $a_t = a_t(y_t, S_t, p_t)$. Since decision problems of this type do not have analytical solutions in general, we need to solve the model numerically. We discretize the state space and use value function iteration to compute optimal decision rules and the corresponding value functions.[13]

INSERT FIGURE 4 HERE

Our computational analysis draws on the example discussed in Orphanides and Zervos (1995). Since our main focus is on studying the impact of beliefs on consumption decisions, we abstract from learning and assume that everybody is of the addictive type. The utility function proposed by Orphanides and Zervos is given by:

$$u(c_t, a_t, S_t) \;\; = \;\; \ln(c_t) \; + \; \ln(a_t) \; + \; S_t^{\psi}(-\phi + \gamma \, a_t) \tag{5.7}$$

where ψ, γ and ϕ are parameters.[14]

We solve the Orphanides-Zervos example under four different assumptions about planing horizons and price expectations. First, we replicate the results reported in Orphanides and Zervos (1995). This case corresponds to an individual who is forward-looking, but assumes that prices will be fixed at one during his or her lifetime. The

[13] Dicretization of the price process implies that we have to approximate the regime switching models by a finite state Markov chain model. Appendix A describes the computational details.

[14] Following Orphanides and Zervos (1995), we set $\phi = 6$, $\gamma = 5.6$, $\psi = 1.0$, $\delta = 0.5$, $\beta = 0.9$. $y_t = 1.0$ for all t.

policy function for that individual is denoted by the dashed line ($-\ -$) in Figure 4. The second case considers an individual who is myopic, ignores the future and faces a price equal to one. The policy function of that individual is denoted by a dotted line (...).

We also consider two additional cases in which individuals are forward-looking and adjust their behavior to take into consideration the possibility of future price increases. The third case models an individual who expects that prices are likely to increase permanently during his or her lifetime. More specifically, the individual believes that there is a twenty percent probability that price will increase from 1.0 to 1.5 in each period. Once prices are at 1.5, they will stay there forever. Thus the Markov transition matrix for that person's beliefs is given by:

$$\begin{bmatrix} 0.8 & 0.0 \\ 0.2 & 1.0 \end{bmatrix} \tag{5.8}$$

The policy function which corresponds to this case is given by the solid line ($-$) in Figure 4.

The last case considers an individual who believes that price increases are transitory in nature. More specifically, we use the following Markov transition matrix to capture the beliefs of this individual:

$$\begin{bmatrix} 0.9 & 0.9 \\ 0.1 & 0.1 \end{bmatrix} \tag{5.9}$$

Price increases are transitory in the sense that there is 90 percent probability that prices will revert back to the lower level in the next period if they are high in the current period. The policy function for these beliefs is given by the line denoted by $(.-)$ in Figure 4.[15]

Figure 4 plots the four different policy functions assuming that individuals currently face the low price. Our findings suggest that the demand for cigarettes declines as we impose more rationality on the individuals. Myopic models have the highest level of demand, whereas forward-looking individuals who anticipate permanent future price increases have the lowest demand. Moreover, we find that the decision rules are sensitive to the assumption we impose on price expectations. If individuals hold constant price expectations, they will consume larger amounts of the addictive good than if they anticipate future price increases. Individuals who assume that price increases are transitory consume more than individuals who anticipate permanent increases. The largest differences in behavior occur for individuals with medium levels of prior cigarette consumption (stock). This is especially relevant for teenagers,

[15] These cases provide natural upper and lower bounds for other models. For example, if individuals are forward looking, but engage in hyperbolic discounting, we would expect that their policy function would lie somewhere between the myopic and the fully rational case.

who are more likely to have to low and medium levels of the addictive stock than adults. We thus conclude that optimal choices in our example depend critically on price expectations and planning horizons.

These results have important policy implications. Another way of interpreting our example is the following: Suppose the government announces that it will implement a policy that will increase cigarette prices by 50 percent. However, the policy announcement is not perceived to be fully credible by all individuals. Some individuals might believe that the policy is not credible at all. These individuals would behave as shown in case 1 or case 2 above. Some individuals may believe that the new policy reflects a permanent shift in policy, but assume that there is only a 20 percent chance that the reform will be enacted in the following period. These individuals would behave as shown in case 3. Finally, some individuals may believe that the policy is not likely to be enacted and only transitory in nature. These individuals would behave as in case 4.

We thus conclude that the behavioral responses of individuals to an announcement or enactment of a new policy crucially depend on how individuals perceive the policies. If policy changes are perceived to be permanent, they can have a large impact on current behavior. If the policy change is perceived to be transitory, the effects are much smaller. If the policy announcement is not credible at all, we would expect almost no behavioral response. Tax policies thus not only affect prices in the period that they are announced or enacted, but they also affect beliefs about future prices. Announced policy changes can have large immediate effects if they are perceived to be credible.[16]

6 Conclusions

Our empirical findings suggest that prices of tobacco products are highly volatile. Consumers face considerable uncertainty about future market conditions. Prices vary significantly among the set of metropolitan areas analyzed in this study. Estimates based on aggregate time series do not reflect the volatility that individuals experience at the local level. Estimated regime switching models suggest that, for a subset of the metropolitan areas considered in this paper, there are two distinctly different regimes of price changes. In the first regime, prices are fairly stable. The second regime is much more volatile and causes large swings in price levels. Young individuals, for whom expenditures on cigarettes comprise a large fraction of their disposable income, will experience large reductions in economic well-being if they do not anticipate future tax and price increases.

These empirical findings raise a number of serious questions regarding the common practice of modelling the demand for cigarettes of teenagers in testing theories of rational addiction. Almost all previous research implicitly assumes that individuals

[16] Gruber and Koeszegi (2001) provide some empirical evidence in favor of this hypothesis.

have perfect foresight. This assumption is not particularly realistic given the volatility of prices. We have shown in this paper how to relax this assumption and extend the basic addiction model to account for price uncertainty. We have provided some examples, which document that behavior of forward-looking individuals can be quite sensitive to beliefs that individuals hold about future prices. These results reinforce the view that tax policies which credibly alter individuals' beliefs about future prices are most effective in reducing teenage cigarette consumption.

A Computation

The policy functions in Figure 4 are approximated as follows. Let p_L and p_H denote the prices in the corresponding states. Here, $p_L = 1.0$ and $p_H = 1.5$. We begin by discretizing the stock variable, S, $S(0), S(1), \ldots, S(n)$, where $S(0) = 0.0$, $S(j+1) = S(j) + \Delta$, $j = 0, \ldots, n-1$, $\delta > 0$, and $n \geq \{(y/p_L)/[(1-\delta)\Delta]\} + 1$. Here, Δ and n were set to 0.001 and 4001, respectively. Next, the addictive good, a, is discretized, $a(j,k,p)$, so that $a(j,k,p) + \delta S(j)$ is equal to some $S(j')$, $0 \leq j' \leq n$, for each k, $0 \leq k \leq m_{j,p}$, and $p = p_L, p_H$. The number $m_{j,p}$ is chosen so that $pa(j, m_{j,p}, p) \leq y$ and $pa(j, m_{j,p} + 1, p) > y$. Note that by conditions placed on n, $a(n, m_{j,p}, p) + \delta S(n) \leq S(n)$. In general, $a(j, k+1, p) = a(j,k,p) + \Delta$, and for δ rational, $a(j + 1/(1-\delta), k, p) = a(j,k,p)$. Hence one only needs to keep track of $a(j, 0, p) = S(j) - \delta S(j)$ and $m_{j,p}$, $j = 0, \ldots, 1/(1-\delta)$, which takes little memory and is computationally fast if $1/(1-\delta)$ is a reasonably small integer. The final step requires the back-fitting algorithm:

$$V_{r+1}(S(j), p_L) = \max_{\{a(j,k,p_L):k=0,\ldots,m_{j,p_L}\}} \{w(p_L, a(j,k,p_L), S(j)) + q_{11} V_r(a(j,k,p_L) + \delta S(j), p_L) + q_{12} V_r(a(j,k,p_L) + \delta S(j), p_H)\},$$

where

$$V_0(S(j), p_L) = \max_{\{a(j,k,p_L):k=0,\ldots,m_{j,p_L}\}} \{w(p_L, a(j,k,p_L), S(j))\}.$$

The $r+1$st policy function approximation with regards to p_L is the corresponding $a(j,k,p_L)$'s that maximize the above equation. The policy function approximation with regards to p_H is obtained similarly. For some $\epsilon > 0$, this process is stopped when

$$\frac{1}{2n} \sum_{j=1}^{n} |V_{r+1}(S(j), p_L) - V_r(S(j), p_L)| + |V_{r+1}(S(j), p_H) - V_r(S(j), p_H)| \leq \epsilon.$$

Here, $\epsilon = 0.001$, although the approximation remains almost unchanged for a much larger Δ and ϵ. Finally, this algorithm can easily be extended to the case of more than two states.

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Figure 1: Prices of Tobacco Products in Levels

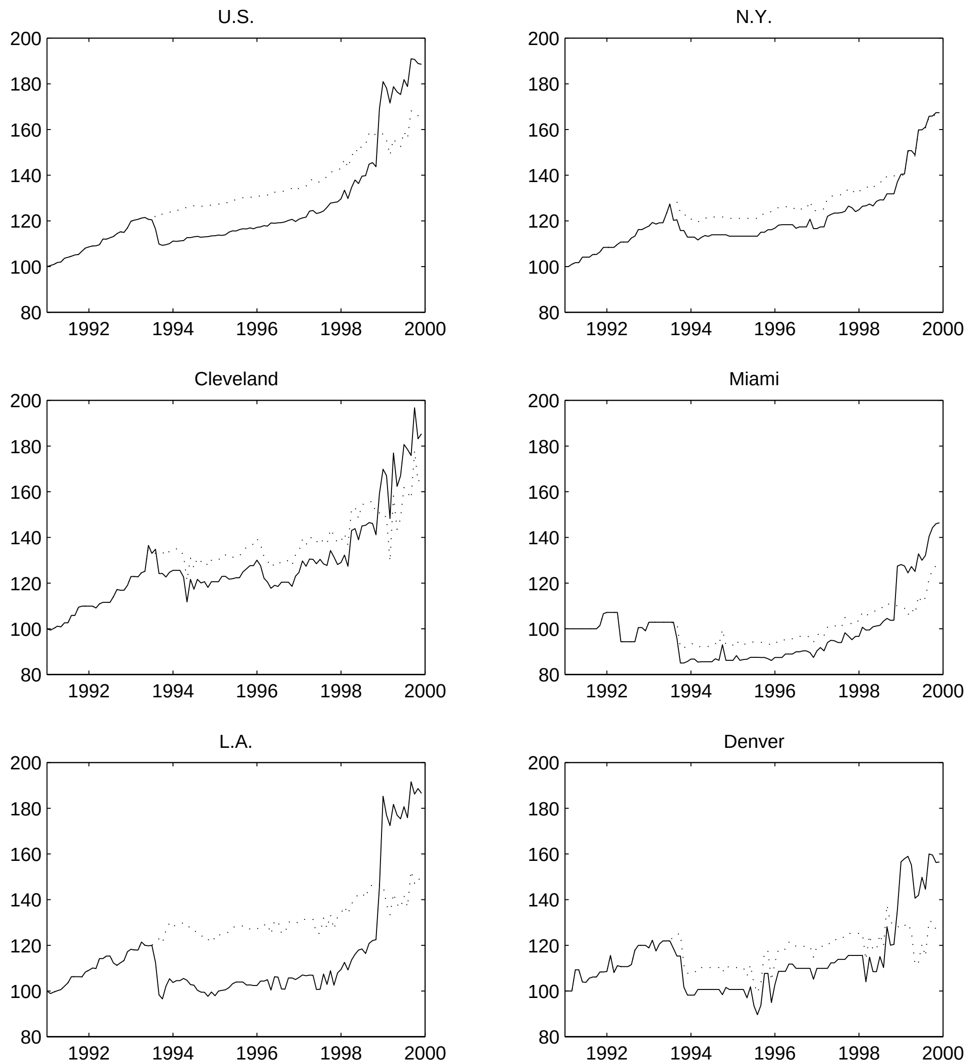


Figure 2: Prices of Tobacco Products in First Differences

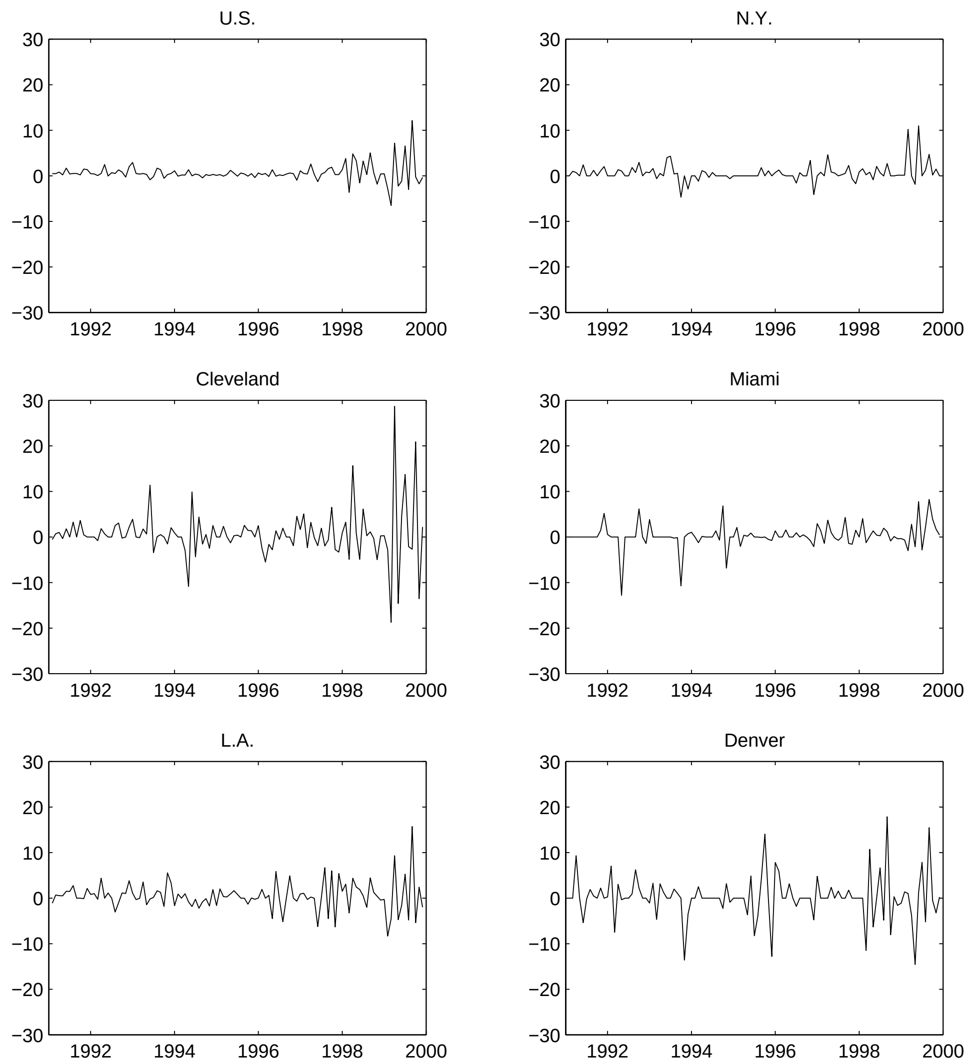
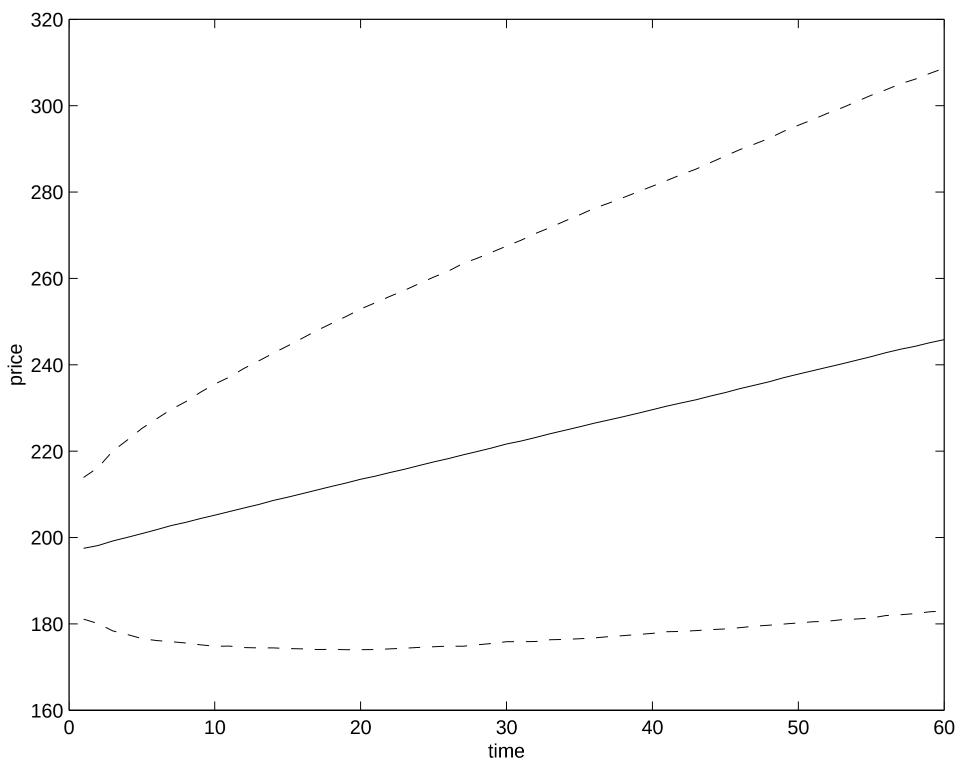


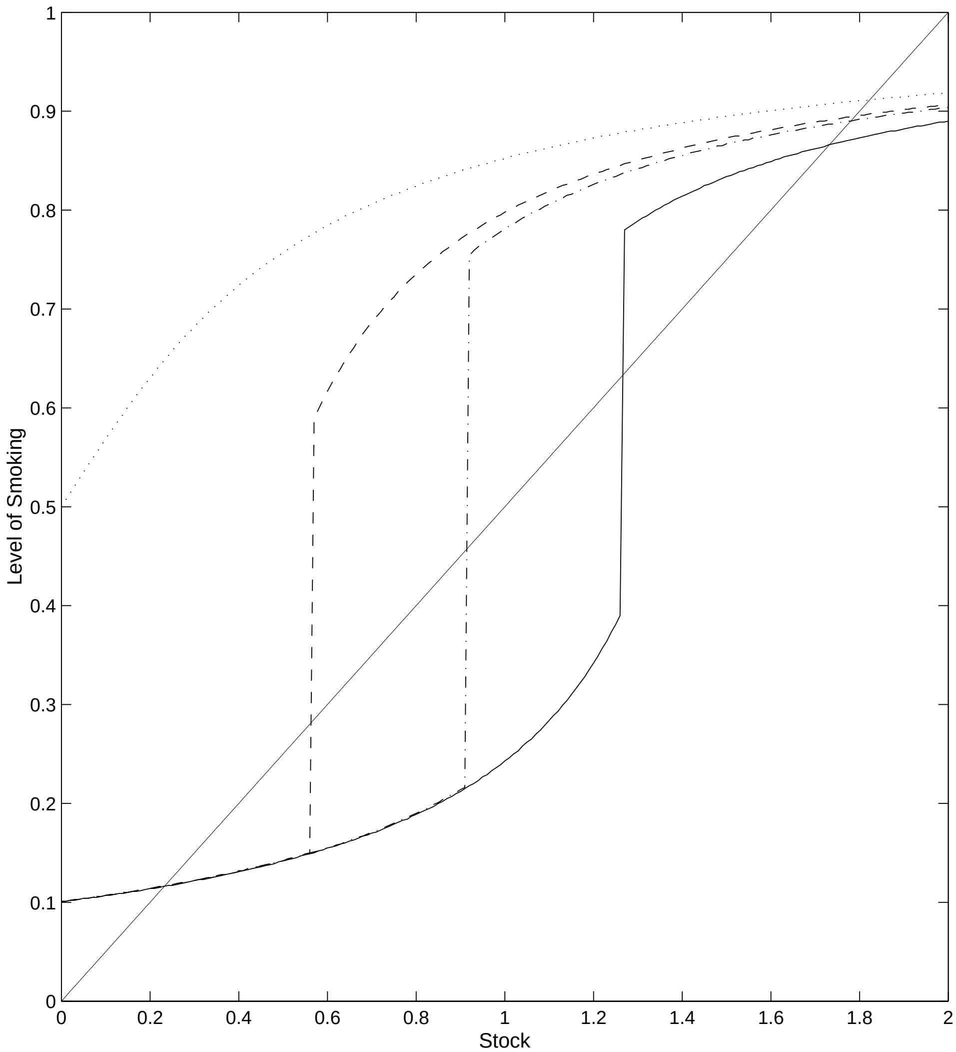
Figure 3: Predicted Prices: Cleveland



Notation:

The solid line (−) shows the predicted mean prices for 60 months. The dashed lines (− −) show the predicted mean plus (minus) two estimated standard deviations.

Figure 4: Policy Functions



Notation:

...	myopic.
– –	forward-looking and constant price expectations.
–.	forward-looking and expectations of transitory price increases.
–	forward-looking and expectations of permanent price increases.