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A Dynamic Model of Rational Addiction: Evaluating Cigarette Taxes

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Addiction creates an intertemporal link between a consumer's past and present decisions, altering their responsiveness to price changes relative to nonaddictive products. We construct a dynamic model of rational addiction and endogenous consumption to investigate how consumers respond to policy interventions that aim to reduce purchases of cigarettes. We find that, on average, the category elasticity is about 35% higher when the model correctly accounts for addiction. However, some policies spur substitution from more expensive single packs to less expensive cartons of cigarettes, resulting in higher overall consumption for some consumers.

Keywords: rational addiction; cigarettes; addictive goods; endogenous consumption; state dependence

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If it were totally up to me, I would raise the cigarette tax so high the revenues from it would go to zero.

(Michael Bloomberg, former mayor of New York City).

1. Introduction

Policymakers are continually searching for new strategies to affect the consumption of harmful products. One possibility is simply to ban a product altogether, as California and other municipalities did with the use of trans fats at restaurants (*Los Angeles Times* 2008). A common alternative to an outright ban is a consumption tax: For example, a variety of taxes exist at both the state and federal levels to curb the consumption of cigarettes, which are known to be both addictive and harmful (U.S. DHHS 1986). The New York City Board of Health chose a different approach when it recently tried (unsuccessfully) to ban the sale of sodas and other sugary drinks in containers exceeding 16 ounces (*New York Times* 2012). Consumers could still have purchased multiple 16-ounce containers in one transaction, but would not have benefited from a quantity discount and the ease of handling a single container.

Short of a complete ban, policymakers require appropriate models of demand to understand how consumers would react to different policies. The magnitude of consumers' demand response is a critical input in choosing the appropriate level of policy intervention. However, studying such policies is difficult due to the addictive nature of many harmful

products, making models of demand for nonaddictive goods inapplicable. Consuming more of an addictive good today reinforces addiction and increases the likelihood of future consumption. Thus addiction influences consumers' decisions by creating a link between past and present consumption utility, which alters their purchasing behavior, incentives to hold inventory, and responsiveness to price changes.

To evaluate the efficacy of different policies, we construct a dynamic model of addiction with endogenous consumption and stockpiling.¹ A consumer's stock of addiction depends on her past consumption and affects her present marginal utility of consumption. The addictive stock decays over time and is replenished by current consumption. Separating consumption quantity from purchase quantity is necessary because the two may diverge in the presence of stockpiling, and addiction should depend only on consumption.

We apply our model to consumer panel data on cigarette purchases. One challenge in examining stockpiling and addiction is that both are unobserved in the data. Before we appeal to the structural model, we present a descriptive analysis (in §3) of variation in the data consistent with stockpiling, addiction, and an interaction between them. Addiction and stockpiling create opposing forms of state dependence: Addiction implies a positive correlation in

¹ Sun (2005), Hendel and Nevo (2006a), and Hartmann and Nair (2010) also model purchase and consumption separately in nonaddictive categories.

purchase quantities over time due to the reinforcing effects of addiction on consumption; stockpiling implies a negative correlation in purchase quantities because holding inventory reduces the need to purchase. With cigarettes, we demonstrate that these correlations exist separately in our data and that the evidence supporting addiction is stronger after controlling for stockpiling behavior. We also consider two nonaddictive categories, i.e., crackers and butter. Although we find evidence consistent with stockpiling in both of these categories, we do not find any patterns consistent with addiction, as expected.

Motivated by the descriptive evidence, we evaluate different specifications that systematically eliminate model components to determine which specification has the most empirical support. We find that a model with addiction and stockpiling is preferred in cigarettes relative to simpler specifications without either process. In contrast, results from a non-nested models test (Vuong 1989) imply that a pure stockpiling model is preferred in crackers and butter.

We use the model to assess the impact of three policies on cigarette purchases. These policies are a tax on premium-tier cigarettes, a category-wide tax, and a ban on the sale of cigarette cartons (consisting of 10 packs). Implementing the first two policies is straightforward, whereas the ban on cartons effectively amounts to eliminating the quantity discount implicit in purchasing a carton. The average pack discount in a carton is about 15%, and over 50% of cigarette purchases are cartons.²

If the model ignores addiction, on average the category elasticity is underestimated by 35%. This underestimation, which partially results from smaller estimates of the price coefficient, helps demonstrate the importance of accounting for addiction when modeling cigarette demand. Interestingly, a category-wide tax yields positive own elasticities for single packs because enough consumers substitute from premium to lower quality packs. This effect is strengthened when cartons are banned, leading some consumers to substitute from premium packs to lower quality cartons which, despite the tax, still have lower unit prices compared to the premium singles.³

We also investigate how consumers respond differently to temporary versus permanent price changes for addictive and nonaddictive goods. The longevity

of the price change affects stockpiling incentives, driving a wedge between short-run consumption and purchase elasticities. In particular, we find an asymmetry: Temporary consumption elasticities are smaller than permanent consumption elasticities due to the smoothing of consumption via addiction. Temporary purchase elasticities are larger than permanent purchase elasticities because addiction creates strong stockpiling incentives to avoid stockouts. In contrast, for nonaddictive goods both consumption and stockpiling inventories are higher for temporary changes than for permanent changes.

Our paper contributes to two streams of research, in marketing and economics, on demand models with state dependence, and measuring the efficacy of taxes on cigarette demand. First, to be clear about terminology, we use the term “state dependence” in its broadest possible interpretation: A consumer’s choice in a period depends on some state variable, which may be observed (e.g., new versus returning customer) or unobserved (e.g., the realization of a private taste shock) to the researcher. Our model considers the specific context where state dependence takes the form of addiction, such that a consumer’s purchase *quantity* today depends on her previous purchase quantities in a manner consistent with the Becker and Murphy (1988) model of rational addiction.⁴

The economics literature uses the terms “addiction” and “habit persistence” interchangeably (Pollack 1970, Iannaccone 1986). In marketing, “habit persistence” typically refers to the relationship between a consumer’s past *probability* of choosing a specific brand and her current choice probabilities (Heckman 1981, Seetharaman 2004, Dubé et al. 2010, Gordon et al. 2013). In Roy et al. (1996), habit persistence implies that the last brand-size combination purchased is more likely to be purchased again.⁵ Addiction, however, differs from this notion of habit persistence in two critical ways. First, the reinforcing effect of addiction implies that past purchase quantities can increase current purchases (Becker and Murphy 1988), whereas models with habit persistence in marketing focus on increases in brand repurchase probabilities. Second, addiction operates at the category level, whereas past work formulates habit persistence at the

²Note that our goal is not to judge which policy is optimal from the policymaker’s perspective. Although our model estimates the demand response to each policy, we lack the data necessary to calculate a measure of consumer welfare that incorporates changes in consumer’s health outcomes, healthcare expenses, and other considerations.

³When cartons are banned, consumers are still permitted to purchase 10 packs but the price per unit is the same as when buying a single pack.

⁴Similarities exist between the Becker and Murphy (1988) model and other work that departs from the standard economic model of decision making. For example, see Hermalin and Isen (2008), who incorporate mood states into an economic model.

⁵Similarly, the model in Guadagni and Little (1983) implies that the last brand-size purchased is more likely to be purchased in the future. However, this outcome is due to positive state dependence in the form of brand and size loyalty terms. In contrast, Roy et al. (1996) use serial correlation in the error terms of the utility-maximizing alternatives across periods to induce persistence in choices.

brand level. Category-level consumption is the most relevant input for determining addiction as opposed to any brand-level factors (Mulholland 1991).

Our work is distinct from much of the literature because of our use of individual-level purchase data combined with a structural model of addiction and stockpiling. In economics, numerous papers test the implications of the Becker and Murphy (1988) model using state-level prices and survey data. Tests of the Becker-Murphy model typically seek to show that higher future prices lead to lower consumption today (Chaloupka 1991, Becker et al. 1994). However, these papers require strong assumptions on consumer expectations and the exogeneity of price changes. The reduced-form models used to implement these tests do not permit the researcher to easily examine alternative policies.⁶

Two recent exceptions are Choo (2001) and Caves (2005). Using annual consumer survey data, Choo estimates a structural model of addiction to study the relationship between a consumer's decision to smoke and her health status. Although our paper lacks information on health status, the higher frequency consumer panel data helps us to disentangle consumers' demand responses to various policy interventions. Caves (2005) estimates a static model of cigarette brand choice to study the interaction between heterogeneity in advertising sensitivity and state dependence, defined as whether a consumer purchased any cigarettes in the previous period. This formulation of state dependence allows Caves to estimate his model using annual aggregate brand-level sales data. However, the model ignores forward-looking behavior and quantity choice, which are critical when studying addictive purchases.

The remainder of this paper is organized as follows. Section 2 discusses the data set and its construction. Section 3 presents descriptive analyses showing that the data can separate stockpiling and addiction behavior in consumers' purchasing patterns. Section 4 presents the model. Section 5 discusses the empirical application, model fit, and results. Section 6 concludes with a discussion of limitations of the present work and avenues for future research.

2. Data

The data are drawn from a Nielsen household panel collected in two separate submarkets in a large Midwestern city over a period of 118 weeks. Each household's purchase history is fairly complete: Purchases across multiple categories are recorded from

all outlets, including convenience stores and gas stations. Including a broad number of channels is important because small retail outlets account for 26% of cigarette sales in our data.⁷

For comparison, we also apply the model to purchase data from two nonaddictive categories, i.e., crackers and butter. The crackers category is particularly apt because, as with cigarettes, crackers are storable and purchased relatively frequently. We include butter for comparison to a less frequently purchased category.⁸ The discussion that follows focuses on our treatment of the cigarette category; we take a similar approach to crackers and butter and refer the reader to Online Appendix A (available as supplemental material at <http://dx.doi.org/10.1287/mksc.2014.0885>) for more details.

Choice models applied to household panel data typically estimate the indirect utility function at the household level. However, preferences and consumption patterns may differ across a household's members. Specifying addiction at the household level would inevitably understate or overstate the importance of addiction for some household members, thus introducing a potential bias. To avoid this issue, we split the household-level observations into individual observations based on the gender and age of the purchaser, recorded with each purchase.⁹

We use the same sample of individuals across the three categories to facilitate cross-category comparison. We select those individuals who made at least 10 cigarette purchases, 10 crackers purchases, and four butter purchases.¹⁰ Of the 1,351 individuals defined at the household-gender-age level who purchased cigarettes at least once, 584 satisfy all of these criteria. These individuals made an average of 44 cigarette purchases across 25,695 purchase observations.

Mapping the data into our model requires a degree of aggregation. First, to keep the study manageable, we classify each product into one of three quality tiers using a combination of classifications found on large

⁷ With that said, it is possible that panelists underreport purchases made at convenience stores and gas stations relative to purchases from their regular shopping trips.

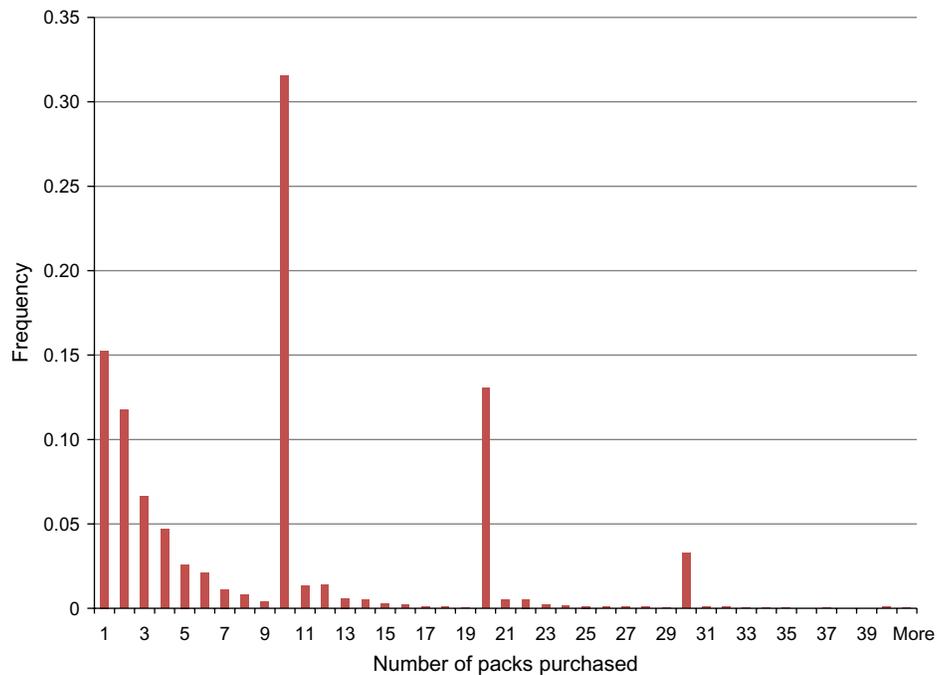
⁸ We avoid a comparison between cigarettes and a perishable product (e.g., yogurt) because perishability introduces a distinct purchase dynamic that might confound the comparison.

⁹ It is still possible that this approach could wrongly attribute cigarette purchases (e.g., if one household member buys all of the cigarettes for the household). To mitigate this risk, we also estimate the model on a sample of single-member households. The parameter estimates for the utility function are qualitatively similar.

¹⁰ Although these cutoffs are admittedly somewhat arbitrary, our goal was to obtain a sample of consumers with sufficient purchase observations in all three categories while not overly restricting the size of the sample. We set a lower cut-off on total butter purchases because the category is purchased less frequently than the other categories.

⁶ Chen et al. (2009) use panel data to understand how consumers adjusted their brand choices following Philip Morris's permanent price cut in April 1993 (known as "Marlboro Friday") in response to the growth of generic brands.

Figure 1 (Color online) Distribution of Purchase Quantity



online retailer websites, and then model consumer choice over tier-quantity combinations. The cigarette category contains numerous distinct brands and several hundred individual products with variants in terms of flavor, strength, and size. Our three quality tiers correspond to common industry classifications of premium, generic, and discount products. We aggregate to the tier level instead of the brand level because our focus is on consumers' overall purchase behavior, rather than on interbrand competition. According to Mulholland (1991) and Viscusi (2003), the taste of cigarettes differs more across quality tiers than across brands within a tier due to varying levels of tar and nicotine. Allowing for brand-level choices would also significantly increase the computational burden of estimating the model.

Second, we create a set of quantity choice bins based on the distribution of cigarette purchase quantities, which appears in Figure 1. The large spikes at 10, 20, and 30 correspond to purchases of one or more cartons, each of which contains 10 packs. Based on this distribution, we discretize purchase quantity into seven bins of {1, 2–4, 5–9, 10, 11–19, 20–24, 25+}. For purchase quantities in the model, we use the midpoint of the first five bins and treat purchases between 20 and 24 as "20" and purchases greater than 25 as "30."

Third, because we lack matched store-level sales data, we only observe the price of the chosen alternative and not the prices of other products in the choice set. We therefore construct the vector of prices

across alternatives based on other panelists' purchases. To ensure that the prices for the alternative options approximate the true levels as closely as possible, we initially fill in prices at the brand level before aggregating to the tier level. We restrict attention to purchases of single packs and cartons as some combination of these items accounts for over 96% of purchases.¹¹ We use the following steps: (1) For a given week, we look for the purchase of a particular brand-size combination in the same store or store format. If such a purchase is found, we use the purchase price for that brand-size combination. (2) If no consumer bought that brand-size that week, we examine adjacent weeks to fill in the price. (3) If no adjacent purchases of the same brand-size are found, we look for purchases of the same brand in a different size during the same week or an adjacent week. We scale this price to the appropriate package size based on the average brand-specific ratio between the per pack price and per carton price found in the channel during the past six months. The ratio of per pack price to the carton price effectively represents the implied quantity discount firms offer for purchasing cartons. (4) If no adjacent purchases of the same brand or brand-size are found, we fill in the price using the price of another brand in the same tier and week. The result is a series of prices across brands for both single packs and cartons.

¹¹ Occasionally two or three packs are sold together in a bundle and some brands sold half-cartons of five packs. We ignore these special package sizes given their low sales volumes.

Table 1 Descriptive Statistics

	Cigarettes		Crackers		Butter	
	Share	Price	Share	Price	Share	Price
High tier	49.18	1.65	33.08	1.91	57.43	1.74
Mid tier	36.66	1.27	44.56	1.70	29.38	1.52
Low tier	14.16	1.11	22.35	1.13	13.19	1.35
Total purchases	25,695		11,906		7,791	

Given the brand-size prices, we aggregate up to the tier-size level by weighing the price of each brand in the tier according to its sales-weighted average. This process produces tier-level prices at the pack and carton level, which we use to form the per unit prices for various quantity combinations.¹² Table 1 provides some descriptive statistics about the categories and product aggregates.

3. Descriptive Analysis

This section provides evidence of moments in the data that separate addiction from stockpiling behavior, demonstrating the necessary variation to identify the structural model. Conceptually, addiction and stockpiling affect a consumer's purchase decision in different ways. In a rational addiction model, past consumption increases the marginal benefit of current consumption, producing a positive correlation between past and current purchase quantities. In contrast, holding stockpiled inventory reduces the incentive to purchase additional quantities, creating a negative dependence between past and current purchase quantities. The challenge in separating addiction and inventory is that neither is observed. We only observe their net effect on the relationship between past and present purchases, which could be positive or negative depending on the relative magnitudes.

Thus, to disentangle addiction and stockpiling we show that our data contain variations consistent with each form of dependence and that an interaction exists between them. First, we demonstrate that each category exhibits purchase behavior consistent with stockpiling based on the relationship between interpurchase times and purchase quantities bought on sale. Second, we only find evidence of addictive purchase patterns in cigarettes where some consumers' purchase quantities tend to increase over consecutive periods. In contrast, a negative relationship exists

between consecutive purchase quantities in crackers and butter. Finally, combining these analyses strengthens our results on increasing purchase quantities in cigarettes and with no interaction in crackers or butter. The contrast in findings across categories suggests that a unique purchase dynamic exists in cigarettes.

3.1. Evidence of Stockpiling Behavior

We follow an approach in Hendel and Nevo (2006b) to identify stockpiling behavior. A standard household inventory model predicts that consumers will buy larger quantities during a sale to stockpile. Table 2 compares average purchase quantities on- and off-sale within each category, where sales are defined as any price at least 5% below the modal price of that universal product code (UPC). The first row in the table shows that purchase quantities on sale are larger in each category, both measured across ("Total") and within consumers ("Within"). The differences between sale and nonsale periods are statistically significant in each category.

Although observing larger purchases during sales is perhaps a necessary condition for stockpiling, a purely static model makes the same prediction (because price sensitive consumers should weakly increase their purchase quantity in response to lower prices). A static model without an inventory state variable does not, however, make any predictions concerning interpurchase duration. A model with stockpiling makes two additional predictions, holding all else equal: (1) the interpurchase duration is longer following a sale because the increase in inventory holdings reduces the consumer's need to purchase; (2) the duration from the previous purchase is shorter for current purchases made on sale because the sale creates an incentive to forward-purchase to add to her inventory.

The second and third rows in Table 2 report the results for these two measures. We focus on the within-consumer estimates since they control for unobserved consumer factors. The second row shows that the duration is shorter between a previous purchase and a current purchase on sale. The third row shows that the duration until the next purchase is larger for current purchases made on sale. The results are fairly consistent across the categories, with a somewhat weaker effect in butter, perhaps reflecting a lower degree of stockpiling behavior in this category.

3.2. Evidence of Addictive Behavior

In a rational addiction model, past consumption increases the marginal utility of current consumption. An implication is that addicted consumers are more likely to increase their successive purchase quantities due to the reinforcing effects of past consumption. Motivated by this, for each consumer we calculate

¹²Our model abstracts away from the channel choice decision because per unit prices for a given tier-quantity combination are similar across channels (see Table 1 in Online Appendix A). This assumption could be problematic if consumers strategically price shop across channels searching for the best deals on different tiers. Incorporating channel choice might be possible if one simplifies the assumed price process, perhaps adopting the simple two-price point formulation in Hartmann and Nair (2010).

Table 2 Descriptive Analysis of Stockpiling

	Cigarettes			Crackers			Butter		
	Sale (diff)			Sale (diff)			Sale (diff)		
	Non-sale	Total	Within	Non-sale	Total	Within	Non-sale	Total	Within
Mean purchase quantity	12.88 (0.31)	4.26 (0.15)	3.73 (0.13)	1.39 (0.01)	0.33 (0.01)	0.27 (0.02)	1.45 (0.02)	0.35 (0.04)	0.21 (0.07)
Weeks from previous purchase	1.89 (0.03)	0.37 (0.04)	-0.45 (0.05)	4.43 (0.04)	1.04 (0.29)	-0.79 (0.31)	5.20 (0.07)	0.98 (0.16)	-0.42 (0.24)
Weeks until next purchase	1.86 (0.04)	0.42 (0.05)	0.50 (0.06)	4.52 (0.04)	1.26 (0.25)	0.92 (0.23)	5.24 (0.06)	0.92 (0.11)	0.37 (0.13)

Notes. The “non-sale” column reports the mean quantities for each row restricted to purchase observations that occurred when the chosen item was not on sale. The next two columns report the difference between non-sale mean and the on-sale mean. The “total” column reports the difference in quantities averaged across all households, whereas the “within” column reports the average difference calculated within a household and then averaged across households. Standard errors are in parentheses.

the probability that a purchase quantity $q_{i,t}$ is smaller, equal, or greater than her previous purchase quantity $q_{i,t-1}$. For example, the probability of increasing purchase quantities for a consumer is $T_i^{-1} \sum T_i I\{q_{i,t-1} < q_{i,t}\}$, where T_i is the number of purchase occasions and $I\{\cdot\}$ is an indicator function.

Table 3 reports these probabilities for each category. The column “All” provides the probabilities averaged over all consumers. None of the differences in increasing versus decreasing probabilities are statistically significant, although the differences are in the opposite directions in cigarettes compared to crackers and butter. It is possible that aggregating over all of the consumers masks cross-sectional heterogeneity in purchase patterns, as suggested by comparing the “Total” and “Within” columns in Table 2. We therefore perform a median split of the sample according to consumers’ total purchase quantities. Because consumers who purchase greater quantities are more likely to be addicted, these consumers may be more likely to exhibit addictive behavior.

The next two columns in Table 3, labeled “Low” and “High” under the “All Purchases” subheading, report results separately for the low- and high-use segments across all purchases. For cigarettes, the high-use segment is significantly more likely to purchase consecutively larger quantities than smaller quantities ($p < 0.001$). In contrast, the analogous differences for crackers and butter are all insignificant and three of four indicate that consumers are more likely to purchase consecutively smaller quantities. Thus, consistent with our intuition, we find evidence supporting addictive behavior in cigarettes and not in crackers or butter.

3.3. Evidence of Addiction and Stockpiling Behaviors

So far we have shown evidence of purchasing dynamics consistent separately with addiction and stockpiling. Next we demonstrate an interaction effect:

Controlling for stockpiling purchases strengthens our results in cigarettes on the probability of increasing purchase quantities. A similar interaction does not exist in crackers or butter, demonstrating that we can separate addiction and stockpiling behavior in our data.

Because stockpiling exerts a negative influence on purchase quantities, removing stockpiled purchases could strengthen the results on purchase quantity acceleration. First we use a simple rule to separate stockpiled and nonstockpiled purchases by comparing the current purchase quantity to the average non-sale purchase quantity (similar to Neslin et al. 1985; see Online Appendix A for details). Next we calculate the purchase quantity acceleration probabilities using the subset of pairs of observations that exclude stockpiled purchases.

The columns under the subheading “Nonstockpiled” in Table 3 report the probabilities of interest for a median split of low- and high-use consumers. Removing the stockpiled purchases leads to a significant purchase quantity effect for both consumer segments (t -statistics of 2.01 and 7.20, respectively). In contrast, for crackers and butter, consumers are more likely to purchase smaller consecutive quantities. The results from cigarettes remain consistent with the Becker and Murphy (1988) model of rational addiction, whereas the tendency for purchasing quantity to decrease in crackers and butter is inconsistent.

In summary, the results in Tables 2 and 3 document the discriminant validity of addiction and stockpiling by showing that not all stockpiling consumers have purchase patterns consistent with addiction. Furthermore, the clear contrast in results across categories highlights a unique purchasing dynamic in cigarettes that does not manifest itself in crackers or butter, which suggests that addiction will not be inferred when it is not expected. This variation aids in the parametric identification of our structural model.

Table 3 Descriptive Analysis of Addiction

Segment	Cigarettes					Crackers					Butter				
	All purchases			Non-stockpiled		All purchases			Non-stockpiled		All purchases			Non-stockpiled	
	All	Low	High	Low	High	All	Low	High	Low	High	All	Low	High	Low	High
Same	0.346	0.341	0.348	0.364	0.379	0.581	0.647	0.550	0.672	0.590	0.622	0.669	0.598	0.716	0.655
Increasing	0.335	0.332	0.336	0.324	0.329	0.207	0.173	0.223	0.163	0.189	0.187	0.159	0.202	0.132	0.167
Decreasing	0.319	0.326	0.316	0.312	0.292	0.212	0.180	0.227	0.165	0.221	0.191	0.173	0.200	0.152	0.178
<i>t</i> -stat	1.177	0.891	3.592	2.016	7.237	-0.654	-0.922	-0.647	-0.508	-7.784	-0.364	-1.023	0.140	-1.954	-1.196
Std. error	0.013	0.007	0.006	0.006	0.005	0.007	0.007	0.006	0.005	0.004	0.010	0.014	0.012	0.010	0.009

Notes. The quantities in the first three rows correspond to the probability that a consumer purchases the same, bigger, or smaller quantities on the current purchase occasion compared to the previous purchase occasion. The row “*t*-stat” reports the test statistic under the null hypothesis that “increasing” equals “decreasing” and the alternative that “increasing” > “decreasing.”

4. Model

This section develops a dynamic model of rational addiction with endogenous consumption and stockpiling. Consumers decide how much to purchase and to consume given their current inventory and addiction levels. Forward-looking behavior is important because consumers are uncertain about whether they will make a store trip next period. If no trip occurs, their next period consumption will be limited to their inventory. In the absence of inventory, the consumer incurs a stockout cost. Consumers’ price expectations also play a role in the simulations in §5.4, where we implement a series of counterfactual tax policies to examine the effect on purchase elasticities.

4.1. Period Utility

Each of $i = 1, \dots, I$ consumers make weekly decisions about which product to purchase, how much to purchase, and how much to consume. The consumption choice c_{it} occurs at the category level and happens every week. Conditional on a store visit, the consumer chooses among $j = 0, \dots, J$ product (tier) alternatives, where choice $j = 0$ represents the no-purchase decision. Let $d_{itjq} = 1$ indicate a choice of product j and quantity q , and let $d_{it} = \{d_{itjq}\}_{jq}$ be the vector of purchase quantity indicators, such that $\sum_{jq} d_{itjq} = 1$.

A consumer’s period of (indirect) utility in state $s_{it} = \{a_{it}, I_{it}, P_t\}$ is the sum of consumption utility, purchase utility, and inventory costs

$$U(c_{it}, d_{it}, s_{it}; \theta_i) = u_c(c_{it}, a_{it}; \alpha_i) + u_p(d_{it}, P_t; \beta_i, \xi_i) - C(I_{it}; h_i), \quad (1)$$

where the stock of addiction $a_{it} \geq 0$ summarizes the cumulative effect of past consumption, $I_{it} \geq 0$ is the consumer’s inventory, $P_t = \{P_{1t}, \dots, P_{Jt}\}$ is a vector of prices, and $\theta_i = \{\alpha_i, \beta_i, \xi_i, h_i\}$ is the parameter vector. Next we discuss each component of the utility function.

Period utility from consumption follows a quadratic form, such that

$$u_c(c_{it}, a_{it}; \alpha_i) = \alpha_{i0}I\{c_{it} = 0\} + \alpha_{i1}c_{it} + \alpha_{i2}c_{it}^2 + \alpha_{i3}a_{it} + \alpha_{i4}a_{it}^2 + \alpha_{i5}a_{it}c_{it}. \quad (2)$$

This functional form allows for the necessary complementarity between consumption and addiction and satisfies standard regularity assumptions in the habit formation literature (Stigler and Becker 1977). Consumption may be zero when inventory is exhausted and the consumer does not make a store trip. The coefficients α_{i0} represent the cost of a stockout or withdrawal,¹³ and α_{i1} and α_{i2} represent the instantaneous utility of consumption independent of addiction. The coefficients α_{i3} and α_{i4} measure the net impact of addiction on present utility. Tolerance may occur at sufficiently high levels of addiction (assuming $\alpha_{i4} < 0$). Finally, if $\alpha_{i5} > 0$, this captures the reinforcement effect that addiction increases the marginal utility of consumption.

The law of motion for a consumer’s stock of addiction is

$$a_{i,t+1} = (1 - \delta_i)a_{it} + c_{it}, \quad (3)$$

where $0 \leq \delta_i \leq 1$ is its depreciation rate. We assume addiction is formed independently of the product tier being consumed. The consumption of any product exerts the same effect on future addiction.¹⁴ Note that this formulation of addiction is different from the marketing literature’s treatment on habit

¹³ Although we do not explicitly model the cessation decision, our model partially captures it because a consumer’s (latent) consumption could be zero in a period. However, with our weekly data set, it is difficult to interpret one period of zero consumption as “quitting.” Multiple consecutive periods of zero consumption may indicate cessation or purchases that the household failed to properly record. Given these concerns we hesitate to interpret such outcomes as indicative of true cessation. Choo (2000) studies the cessation decision explicitly using annual survey data.

¹⁴ Nicotine is the primary substance in cigarettes that leads to addiction, the amount of which varies across tiers. An alternative would be to make a consumer’s addictive stock a function of the amount of nicotine consumed as opposed to the number of cigarettes consumed, although these quantities should be positively correlated. The model could be further extended to allow the evolution of addiction to depend on other brand-specific characteristics such as tar levels. However, research by Rose (2006) also suggests that non-nicotine factors, such as the sensory stimulation from smoking, may play a role in cigarette addiction.

persistence (discussed in §1). That work focuses on the persistence of brand choice and ignores quantity choice, making it difficult to capture the reinforcing effects of past consumption on current decisions. Furthermore, these models do not incorporate the quantity decision necessary to capture the reinforcing effects of past consumption on current decisions.

In addition to consumption, consumers simultaneously choose to purchase from among a discrete set of tier-quantity combinations. Purchase utility is

$$u_p(d_{it}, P_t; \beta_i, \xi_i) = \sum_{j,q} d_{itjq} (\beta_i p_{tjq} q_{itj} + \xi_{itjq} + \varepsilon_{itjq}), \quad (4)$$

where q_{itj} is the purchase quantity, p_{tjq} is the price per unit, $p_{itjq} q_{itj}$ is the total expenditure, and β_i measures price sensitivity. The price per unit p_{tjq} is specific to a tier and quantity, which allows for nonlinear pricing (see §4.2). We account for product-level differentiation through the fixed-effects ξ_{itjq} and ε_{itjq} is an unobserved shock to utility that is distributed i.i.d. extreme value.¹⁵

Quantities purchased in the current period are available for immediate consumption. Those not consumed are stored at a holding cost of h_i , such that $C(I_{it}; h_i) = h_i \cdot I_{it}$. All units held in inventory are identical; inventory does not keep track of the mix of tiers previously purchased. Inventory evolves according to

$$I_{i,t+1} = I_{it} + \sum_{j,q} d_{itjq} q_{itj} - c_{it}. \quad (5)$$

Next we discuss how consumers form expectations about future prices and store visits. We then formulate the consumer's dynamic decision problem.

4.2. Price Expectations

Consumers make tier and quantity decisions based on their expectations of future prices. They believe that the underlying relationship between tier prices and tier-quantity prices is stable, and use these values to generate expectations about the stochastic evolution of prices for each potential choice. Given the importance of quantity discounts in these categories, we allow the price per unit to vary across quantities.

Our specification follows that found in Erdem et al. (2003). The unit price for a tier depends on its last

period price and competitors' prices. Let P_{tj} denotes the price per unit in tier j and let p_{tjq} be the price per unit for q units of tier j (i.e., if $q = 1$, then $P_{tj} = p_{tjq}$). The tier-level price per unit follows a first-order Markov process,

$$\ln(P_{tj}) = \gamma_{1j} + \gamma_{2j} \ln(P_{t-1j}) + \gamma_{3j} \frac{1}{J-1} \sum_{l \neq j} \ln(P_{t-1l}) + \nu_{tj}, \quad (6)$$

where price competition enters through the mean log price of competing tiers and $\nu_t = [\nu_{t1}, \dots, \nu_{tJ}]' \sim N(0, \Sigma_\nu)$. Diagonal elements in Σ_ν capture correlation over time in tier prices.

The system above describes the process governing unit prices for each tier. In the data we observe that price per unit weakly declines in purchase quantity. To allow for this nonlinear pricing, we further model consumer expectations at the tier-quantity level. Consumers form these expectations based on the single unit tier price P_{tj} . The price process for a specific quantity $q > 1$ of tier j is

$$\ln(p_{tjq}) = \lambda_{1jq} + \lambda_{2jq} \ln(P_{tj}) + \nu_{tjq}, \quad (7)$$

where $\nu_{tjq} \sim N(0, \sigma_{jq}^2)$. This formulation reduces the state space of the dynamic consumer problem from JQ tier-quantity prices to J tier prices, while still allowing the per-unit prices to vary by tier.

4.3. Store Visits

In the data we observe trips made to the store, and conditional on a store visit, whether a purchase was made in a category. Rather than incorporating the store visit decision into a consumer's dynamic choice problem, we assume visits follow an exogenous binomial distribution that depends on whether a store was visited in the previous period.¹⁶

Let π_{it} indicate whether a store visit occurs in t and $\rho_{i1} = \Pr(\pi_{it+1} = 1 \mid \pi_{it} = 1)$ is the probability of visiting a store next period conditional on a store visit this period. Similarly, $\rho_{i0} = \Pr(\pi_{it+1} = 0 \mid \pi_{it} = 0)$ is the probability of not visiting a store next period conditional on not visiting a store this period. We estimate these probabilities at the consumer level directly from the observed store visit frequencies and treat their values as known in the dynamic estimation. Note that,

¹⁵ Our assumption that ε_{itjq} are i.i.d. deserves an additional comment because it implies that the errors are independent across purchase sizes. Although the i.i.d. assumption is commonly made for tractability in similar modeling settings (e.g., Hendel and Nevo 2006a), it is not innocuous. In reality we expect such errors to be correlated across sizes: A large positive shock for $q = 20$ packs likely implies a large shock for $q = 10$ packs. A related issue is that welfare estimates in our setting would likely be overestimated. Adding choices to the set of possible quantities would increase consumer welfare even though the additional choices may simply be different quantity bundles of the same product (and not actually new products with potentially new unobserved characteristics that might offer some welfare benefits).

¹⁶ A more sophisticated model would include the choice to visit a store in the consumer's dynamic decision problem. This might be appropriate in the cigarette category since addictive products are probably more likely to motivate store trips than nonaddictive consumer packaged goods such as yogurt or ketchup. However, including the store visit decision further complicates the model, so we leave it to future research. A related issue is highlighted in Ching et al. (2009), who consider a model in which consumers decide whether to consider a category based on their inventory and price expectations.

conditional on a store visit, a consumer still chooses whether to purchase in the category or to select the $j = 0$ no-purchase option.

4.4. Dynamic Decision Problem

Consumers solve an infinite time horizon dynamic programming problem. Given their current state, period utility function, and expectations about future prices and store visits, consumers simultaneously make their optimal tier-quantity d_{itjq}^* and consumption c_{it}^* decisions. The value function when a consumer visits a store is $V(s_{it})$ and the value function without a store visit is $W(s_{it})$. We assume that the discount factor is fixed and known at $\beta = 0.995$. The Bellman equation during a period with a store visit is

$$V(s_{it}) = \max_{c_{it}, d_{it}} \left\{ U(c_{it}, d_{it}, s_{it}; \theta) + \beta \mathbb{E}[\rho_{i1} V(s_{it+1}) + (1 - \rho_{i1}) W(s_{it+1}) | s_{it}] \right\} \quad (8)$$

s.t.

$$0 \leq c_{it} \leq I_{it} + \sum_{j,q} d_{itjq} q_{it} \quad \text{and} \quad \sum_{j,q} d_{itjq} = 1, \quad (9)$$

where the expectation is over the conditional distribution of future prices given state s_{it} . During a period without a store visit, the consumer's value function is

$$W(s_{it}) = \max_{c_{it}, d_{it}} \left\{ u_c(c_{it}, a_{it}; \alpha_i) - C(I_{it}; h_t) + \beta \mathbb{E}[\rho_{i0} V(s_{it+1}) + (1 - \rho_{i0}) W(s_{it+1}) | s_{it}] \right\} \quad (10)$$

$$\text{s.t. } 0 \leq c_{it} \leq I_{it}. \quad (11)$$

We solve the value functions for the optimal consumption conditional on a tier choice

$$c_{it}^* = \arg \max_{c_{it}} \left\{ U(c_{it}, d_{it}^*, s_{it}; \theta) + \beta \mathbb{E}[\rho_{i1} V(s_{it+1}) + (1 - \rho_{i1}) W(s_{it+1}) | s_{it}] \right\} \quad (12)$$

$$\text{s.t. } 0 \leq c_{it} \leq I_{it} + d_{it}^* q_{it}, \quad (13)$$

where d_{it}^* is a vector with a one in the position of $d_{itjq}^* = d_{itjq}^*$ and zero elsewhere. Because the inventory state variable is not tier-specific, the optimal consumption level is independent of tier choice conditional on a purchase quantity. This observation simplifies computing the policy functions by reducing the number of one-dimensional optimizations over consumption.

4.5. Heterogeneity and Estimation

We estimate the model using maximum likelihood. To account for heterogeneity, each consumer belongs to one of M unobserved preference segments with probability ϕ^m . The probability a consumer is of type m is

$$\phi^m = \frac{\exp(\delta_m)}{1 + \sum_{m'=2}^M \exp(\delta_{m'})}, \quad (14)$$

where δ_m , for $m = 2, \dots, M$, are a set of parameters to be estimated.

Let $T_i \subseteq T$ be the set of time periods in which consumer i made a store visit. We can only evaluate the likelihood for each $t \in T_i$. Let D_{it} be the observed tier-quantity decision at time t and $\theta = \{\theta_1, \dots, \theta_M\}$ be the dynamic parameters of interest. Given the extreme value distribution of the error term ε , the probability consumer $i \in m$ makes decision d_{itjq} at time $t \in T_i$ is

$$\Pr(D_{it} = d_{itjq} | a_{it}, I_{it}; \theta_m) = \frac{\exp(V_{itjq}^m(s_{it}; \theta_m))}{\sum_{j', q'} \exp(V_{ij'q't}^m(s_{it}; \theta_m))}, \quad (15)$$

where $V_{itjq}^m(s_{it}; \theta_m)$ is the value function for choice d_{itjq} ,

$$V_{itjq}^m(s_{it}; \theta_m) = \max_{c_{it}} \left\{ U(c_{it}, d_{it}, s_{it}; \theta_m) + \beta \mathbb{E}[\rho_{i1} V^m(s_{it+1}; \theta_m) + (1 - \rho_{i1}) W^m(s_{it+1}; \theta_m) | s_{it}] \right\}, \quad (16)$$

which solves for the optimal consumption c_{it}^* given the tier-quantity choice. The likelihood contains the unobserved addiction and inventory state variables. Given initial conditions, the model permits us to calculate laws of motion for addiction and inventory using the policy functions.

The individual-level likelihood function for a consumer in segment m is

$$L(D_{i1}, \dots, D_{iT} | s_{i1}, \dots, s_{iT}; \theta_m) = \int \left(\prod_{t \in T_i} \Pr(D_{it} = d_{itjq}^* | a_{it}, I_{it}; \theta_m) \right) dF(a_{i0}, I_{i0}), \quad (17)$$

where $F(a_{i0}, I_{i0})$ is the initial joint density of addiction and inventory levels. The log-likelihood function over all households is

$$L(D | s; \theta) = \sum_{i=1}^I \log \left(\sum_{m=1}^M \phi^m L(D_{i1}, \dots, D_{iT} | s_{i1}, \dots, s_{iT}; \theta_m) \right). \quad (18)$$

Additional details on the computation and estimation can be found in Online Appendix B.

5. Empirical Application

This section begins with a discussion of model fit and selection, after which we present the parameter estimates from the preferred set of models and the associated policy functions. The remainder of this section discusses our counterfactual pricing experiments.

Table 4 Model Fit Statistics for Cigarettes

No. of segments	Model 1			Model 2			Model 3		
	1	2	3	1	2	3	1	2	3
–LL	69,964	69,388	69,326	69,473	69,354	69,342	69,749	69,328	69,312
AIC	69,990	69,441	69,406	69,499	69,407	69,422	69,779	69,389	69,404
BIC	70,021	69,505	69,502	69,530	69,471	69,518	69,815	69,463	69,515
χ^2		0.000	0.000		0.000	0.630		0.000	0.417

Notes. Likelihood-based model fit statistics for each model specification with a different number of discrete segments. Bottom row reports the χ^2 -statistic that compares two adjacent models, assuming the larger model is correctly specified.

5.1. Model Evaluation and Comparison

We estimate three specifications to demonstrate the importance of the model's components: Model 1 (M1) is a dynamic model of endogenous consumption and stockpiling without addiction; model 2 (M2) is a dynamic addiction model without inventory such that all purchases must be consumed immediately; model 3 (M3) is the full model with both addiction and stockpiling.¹⁷

We assess model fit in terms of choosing the optimal number of segments and determining which model the data support best. For simplicity, we select the number of segments based solely on results in the cigarette category, using this number of segments for crackers and butter. Table 4 reports likelihood-based fit statistics in cigarettes for all of the models with up to three preference segments. Based on the BIC, a three-segment specification is marginally preferred under M1, whereas two segments are preferred under models M2 and M3. Given the small decrease in Bayesian information criterion (BIC) from two to three segments under M1, we use two segments for the rest of our analysis. Table 4 also reports Vuong tests, conditional on a model, that select the appropriate number of segments. The Vuong test reduces to the standard likelihood ratio (LR) test under the assumption that the larger model is correctly specified, so that the bottom row of Table 4 includes the χ^2 -statistics from tests between models with a differing number of segments. The conclusions from comparing the BICs and the Vuong tests are consistent. In the subsequent discussion, we refer to segments 1 and 2 as the heavy-use and light-use segments, respectively.

Given the number of segments, we compare the three model specifications. Under the assumption that M3 is the true model for cigarettes, an LR test can determine which model the data best support because M1 and M2 are nested within M3. The test evaluates the null hypotheses $H_0: M1 \equiv M3$ and $H_0: M2 \equiv M3$ versus the alternatives that M3 is preferred over

Table 5 Model Fit Statistics

	Model 1	Model 2	Model 3
Cigarettes			
–LL	69,388	69,354	69,328
AIC	69,441	69,407	69,389
BIC	69,505	69,471	69,463
Crackers			
–LL	31,147	31,188	31,140
AIC	31,168	31,211	31,169
BIC	31,190	31,235	31,198
Butter			
–LL	22,882	22,895	22,877
AIC	22,903	22,918	22,906
BIC	22,923	22,940	22,933

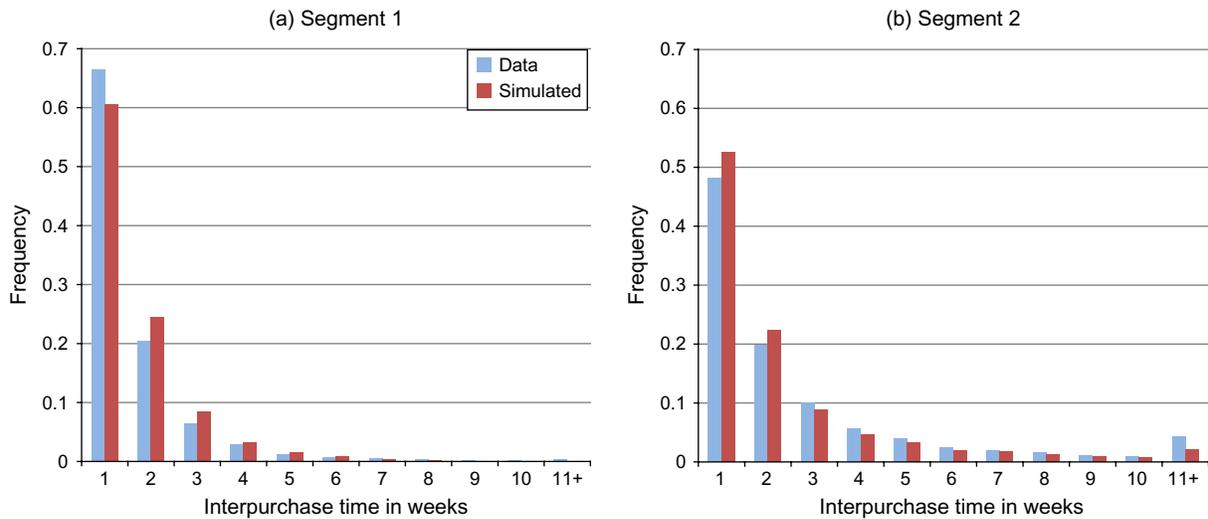
either restricted model.¹⁸ Both tests reject the null in favor of the unconstrained model (for M1 versus M3, $\chi^2 = 120$, $p < 0.001$ and for M2 versus M3, $\chi^2 = 52$, $p < 0.001$). The same can be seen comparing the BICs across models in Table 5, which shows that M3 is preferred for cigarettes but M1, the pure stockpiling model, is preferred for the other two categories.

However, to assess model fit in crackers and butter is more complicated because M1 and M2 are non-nested: The models share a common set of parameters and have parameters unique to their specifications, making them overlapping models. We use the framework in Vuong (1989), which handles both nested and non-nested model comparisons, to compare the specifications in the other categories. When the models are nested, Vuong's test reduces to an LR test. With overlapping models, the limiting distribution of the test statistic is a weighted sum of chi-squared distributions (Vuong 1989, §6). Under the assumption that M1 is the true model for the nonaddictive categories, a test of overlapping models evaluates the hypothesis that $H_0: M1 \equiv M2$ against the pair of alternative hypotheses that H_{1A} : "M1 preferred over M2" and H_{1B} : "M2 preferred over M1." We reject the null hypotheses for both nonaddictive categories in favor

¹⁷ For more details on M1 and M2, and an extensive Monte Carlo study, please refer to Online Appendix C.

¹⁸ Formally, the null hypotheses specify that the nonoverlapping parameters between M1 (or M2) and M3 are jointly equal to zero, implying that the models are equivalent if the null is not rejected.

Figure 2 (Color online) Distribution of Interpurchase Times (in Weeks) by Segment for Cigarettes



of the alternatives that prefer M1 over M2 (for crackers $V = 82, p = 0.004$, and for butter $V = 26, p = 0.03$). A second set of (nested) tests determines whether the pure stockpiling model is preferred over the full model with stockpiling and addiction ($H_0: M1 \equiv M3$ versus $H_1: "M3 preferred over M1"$). We fail to reject the null hypotheses and conclude that modeling addiction is unnecessary in the crackers and butter categories (for crackers $\chi^2 = 14, p = 0.09$, and for butter $\chi^2 = 10, p = 0.27$). These tests are consistent with the BIC comparisons in Table 5, which support a preference for the pure stockpiling model in the non-addictive categories. Thus, the models with addiction (M2 and M3) do not provide additional explanatory power for crackers and butter, where we would not expect addiction to exist. In contrast, the addictive process improves the model's fit for cigarettes.

We also compare the simulated and observed distributions of purchase quantities and interpurchase times for each segment. Figure 2 shows that our model fits the interpurchase distribution well, and that the distribution for the heavy use segment is shifted to the left, indicating shorter interpurchase times on average. Figure 3 demonstrates that the model produces reasonable simulated outcomes across the purchase quantities and segments. The heavy use segment consumes a significantly higher quantity of cigarettes compared to the light use segment. Heavy smokers purchase cigarette cartons at about the same frequency that light smokers purchase a single pack of cigarettes, despite the fact that, according to Figure 2, the heavy use segment has a slightly shorter interpurchase time.

5.2. Parameter Estimates

Table 6 reports the parameter estimates in each category for each of the three models. We start with a

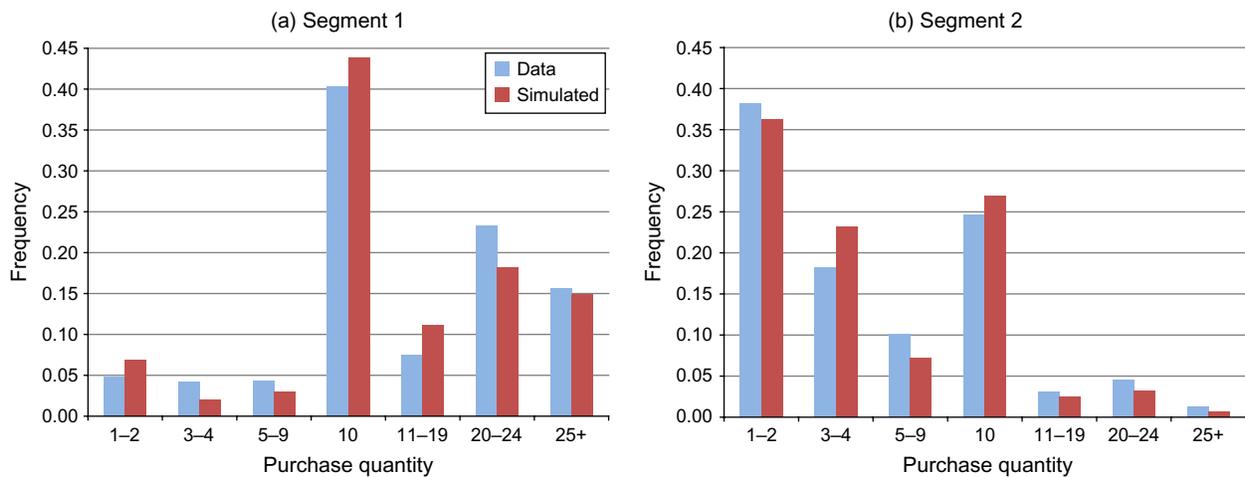
discussion of the estimates for cigarettes, comparing the results in M3 to those using the other two models that eliminate addiction and stockpiling, respectively. Then we contrast the cigarette estimates to those from crackers and butter. Estimates for the price processes appear in Online Appendix B.

For cigarettes, the addiction depreciation coefficients (δ_i) are significant indicating that past consumption quantities affect current decisions. The signs on the addiction terms are consistent with the theory that addiction creates a reinforcing effect between past and current consumption. The coefficient on the interaction between consumption and addiction (α_{15}) is positive for both segments, implying that past consumption increases the marginal utility of present consumption (Becker and Murphy 1988).

The parameter estimates differ between the consumer segments. Consumers in the heavy-use segment receive less instantaneous utility from consumption, have a higher marginal utility for addictive consumption, are less price sensitive, and have higher stockout costs. The mean of the addiction level for a heavy-use consumer is 4.83 and for a light-use consumer is 2.08. The heavy-use segment has a higher stockout cost (\$9.07) compared to the light-use segment (\$3.95). Inventory holding costs of \$0.30 and \$0.26, respectively, are about the same for each segment.

Next we compare the full model (M3) to the model with stockpiling and no addiction (M1). First, including addiction increases the price coefficients for both segments by roughly 30%. Ignoring addiction leads the model to underestimate price sensitivity because addiction helps account for some lack of responsiveness in demand to price changes. Similar intuition exists in the Keane (1997) study of positive state dependence for (nonaddictive) consumer packaged goods. Second, the model without addiction partially

Figure 3 (Color online) Distribution of Purchase Quantity by Segment for Cigarettes



rationalizes an observed rate of consumption with lower inventory holding costs and higher stockout costs, both of which create incentives to purchase larger quantities.

The parameter estimates are, however, similar across models M1 and M3 in the crackers and butter categories (consistent with the model fit statistics in Table 5). Most of the addiction terms in M3 are insignificant; the linear addiction term in segment 1 is statistically significant but its magnitude renders it economically unimportant. These estimates do not indicate any behavior consistent with a rational addiction model because they do not support a positive relationship between past and current consumption (α_{15} is insignificant). The average stockout costs are \$0.91 and \$0.39 for crackers and butter, respectively, which are much lower compared to cigarettes. It is possible that the stockout cost estimates for cigarettes include a psychological cost component associated more with addictive goods.

5.3. Purchase and Consumption Policy Functions

The impact of addiction can be seen directly by comparing the policy functions from the full model (M3) for cigarettes and crackers. Figures 4(a) and 4(b) plot the consumption and purchase policy functions averaged over all consumers as a function of inventory and addiction. Figures 5(a) and 5(b) depict the corresponding policy functions for crackers.

Consider the variation in consumption along the inventory dimension for a fixed level of addiction. At low levels of addiction, the relationship is similar to prior work in nonaddictive goods where consumption increases at a declining rate with inventory due to holding costs (Ailawadi and Neslin 1998, Sun 2005). Consumers adjust their consumption to preserve inventory in the event of a future stockout. However, at higher levels of addiction, the reinforcement effect

and holding costs lead to a monotone increase in consumption. Next consider the variation in consumption through addiction given a fixed inventory. For low inventory, consumption has an inverted-U relationship with addiction, whereas with a high inventory, consumption strictly rises with addiction because of higher holding costs and the reinforcement effect.

The purchase policy function in Figure 4(b) exhibits a similar shape at low levels of addiction and inventory. At high addiction levels, purchase quantities decrease with inventory even as consumption increases, leading the consumer to draw down her inventory. Purchase quantity increases with addiction at low levels of inventory, even though consumption decreases at high levels of addiction. At high levels of inventory, purchase quantity eventually resembles an inverted-U shape as a function of addiction due to the opposing forces of the reinforcement effect and excess addiction.

The policy functions for crackers differ from those of cigarettes. Neither policy function for crackers exhibits any significant variation in the addiction dimension. Consumption increases steadily as inventory rises but is unresponsive to addiction. Purchase quantity rises and eventually falls when inventory becomes sufficiently high. The shape of these policy functions is consistent with our expectations for nonaddictive goods, whereas the results for cigarettes demonstrate the impact of addiction on consumers' consumption and purchase decisions.

5.4. Counterfactual Pricing Experiments

This subsection evaluates a series of policies that raise retail cigarette prices. First, we consider a set of policies that vary in their breadth of application, i.e., premium tier, category, and cartons. Second, assuming a tax on the premium tier, we investigate how the longevity of the tax affects the demand response. In

Table 6 Parameter Estimates

	Cigarettes			Crackers			Butter		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Segment 1 (heavy-use)									
Consumption (α_1)	0.1811 (0.0042)		0.1302 (0.0033)	0.2528 (0.0063)		0.2861 (0.0148)	0.0890 (0.0103)		0.0839 (0.0137)
Consumption ² (α_2)	-0.0030 (0.0003)		-0.0021 (0.0004)	-0.0029 (0.0003)		-0.0024 (0.0003)	-0.0004 (0.0002)		-0.0004^a (0.0002)
Stockout cost (α_0)	0.8971 (0.0476)		0.7641 (0.0406)	0.2930 (0.0496)		0.2840 (0.0594)	0.0476 (0.0099)		0.0440 (0.0142)
Holding cost (h)	0.0146 (0.0061)		0.0255 (0.0092)	0.0988 (0.0211)		0.1024 (0.0344)	0.0282 (0.0038)		0.0206 (0.0053)
Addiction (α_3)		0.0521 (0.0202)	0.1129 (0.0192)		0.0043 (0.0027)	0.0070 (0.0042)		0.0120 (0.0758)	0.0110 (0.0863)
Addiction ² (α_4)		-0.0298 (0.0034)	-0.0377 (0.0028)		0.0006 (0.0005)	0.0012 (0.0017)		-0.0001 (0.0001)	-0.0001 (0.0001)
Consumption * Addiction (α_5)		0.0543 (0.0202)	0.0841 (0.0120)		0.0087 (0.0063)	0.0095 (0.0082)		-0.0005 (0.0008)	-0.0008 (0.0007)
Addiction depreciation (δ)		0.5253 (0.1730)	0.5190 (0.1873)		0.5193 (0.2380)	0.5098 (0.2811)		0.5079 (0.2754)	0.5023 (0.2844)
Price (β)	-0.0652 (0.0047)	-0.0703 (0.0085)	-0.0842 (0.0059)	-0.2975 (0.0280)	-0.2870 (0.0435)	-0.3189 (0.0221)	-0.1283 (0.0077)	-0.1313 (0.0093)	-0.1379 (0.0080)
Segment 2 (light-use)									
Consumption (α_1)	0.2187 (0.0050)		0.1576 (0.0014)	0.2021 (0.0149)		0.1902 (0.0320)	0.1042 (0.0150)		0.0765 (0.0246)
Consumption ² (α_2)	-0.0009 (0.0001)		-0.0012 (0.0001)	-0.0002 (0.0001)		-0.0001 (0.0000)	-0.0002 (0.0001)		-0.0005 (0.0002)
Stockout cost (α_0)	0.6498 (0.0307)		0.5535 (0.0268)	0.3108 (0.0341)		0.3467 (0.0412)	0.0588 (0.0142)		0.0480 (0.0167)
Holding cost (h)	0.0224 (0.0059)		0.0364 (0.0080)	0.1512 (0.0339)		0.1366 (0.0240)	0.0262 (0.0050)		0.0232 (0.0112)
Addiction (α_3)		0.0721 (0.0289)	0.0818 (0.0083)		0.0284 ^a (0.0153)	0.0511 (0.0359)		-0.0007 (0.0016)	-0.0007 (0.0028)
Addiction ² (α_4)		-0.0332 (0.0022)	-0.0220 (0.0011)		-0.0008 (0.0007)	-0.0009 (0.0008)		-0.0001 (0.0001)	-0.0001 (0.0001)
Consumption * Addiction (α_5)		0.0168 (0.0032)	0.0232 (0.0088)		0.0143 (0.0137)	0.0172 (0.0119)		0.0025 (0.0032)	0.0030 (0.0037)
Addiction depreciation (δ)		0.5241 (0.1465)	0.5175 (0.1328)		0.5204 (0.1616)	0.5122 (0.2078)		0.5260 (0.3200)	0.5325 (0.3132)
Price (β)	-0.1105 (0.0056)	-0.1210 (0.0107)	-0.1403 (0.0079)	-0.3598 (0.0290)	-0.3205 (0.0456)	-0.3748 (0.0395)	-0.1482 (0.0142)	-0.1512 (0.0137)	-0.1535 (0.0098)
Segment 1 size	0.3783 (—)	0.2807 (—)	0.3215 (—)	0.4004 (—)	0.3421 (—)	0.4232 (—)	0.2512 (—)	0.2354 (—)	0.2933 (—)
Segment 2 size	0.6217 (0.0378)	0.7193 (0.0412)	0.6785 (0.0365)	0.5996 (0.0304)	0.6579 (0.0418)	0.5768 (0.0243)	0.7488 (0.0373)	0.7646 (0.0399)	0.7067 (0.0158)

Notes. Standard errors are in parentheses. Estimates of fixed effects (ξ_{ij}) excluded due to space. Bolded estimates indicate significance at the 95% level or higher. A superscript ^a indicates weak significance at the 90% level.

both cases our goal is to explore how purchase behavior changes under each policy and to compare the results to those obtained using a model that ignores addiction.¹⁹

¹⁹ Policymakers' motivations for implementing taxes on items such as cigarettes are mixed. Raising revenue is a dominant public motivation underlying recent cigarette taxes. For example, the stated goal of the federal cigarette tax increase in April 2009 was to finance expanded health care for children (*USA Today* 2012). However,

5.4.1. Tax Experiments. We consider three types of policy interventions. First, a 10% tax on all premium-tier cigarettes, akin to a luxury tax on a

policies such as the attempted New York City ban on large soda containers mostly have a social component since no tax is being implemented, although one long-term goal is to reduce healthcare expenses. Given that our analysis is unable to quantify the potential health benefits of implementing these policies, we leave to future research the goal of developing appropriate welfare measurements to help guide such policy choices.

Figure 4 (Color online) Consumption and Purchase Decision Functions for Cigarettes

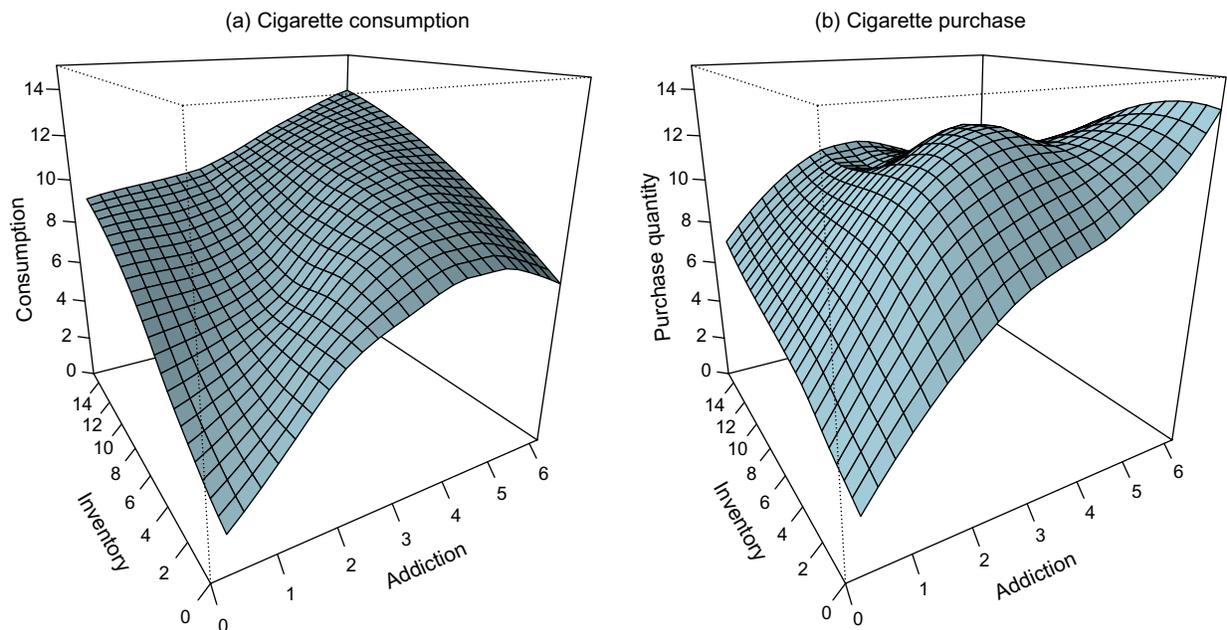
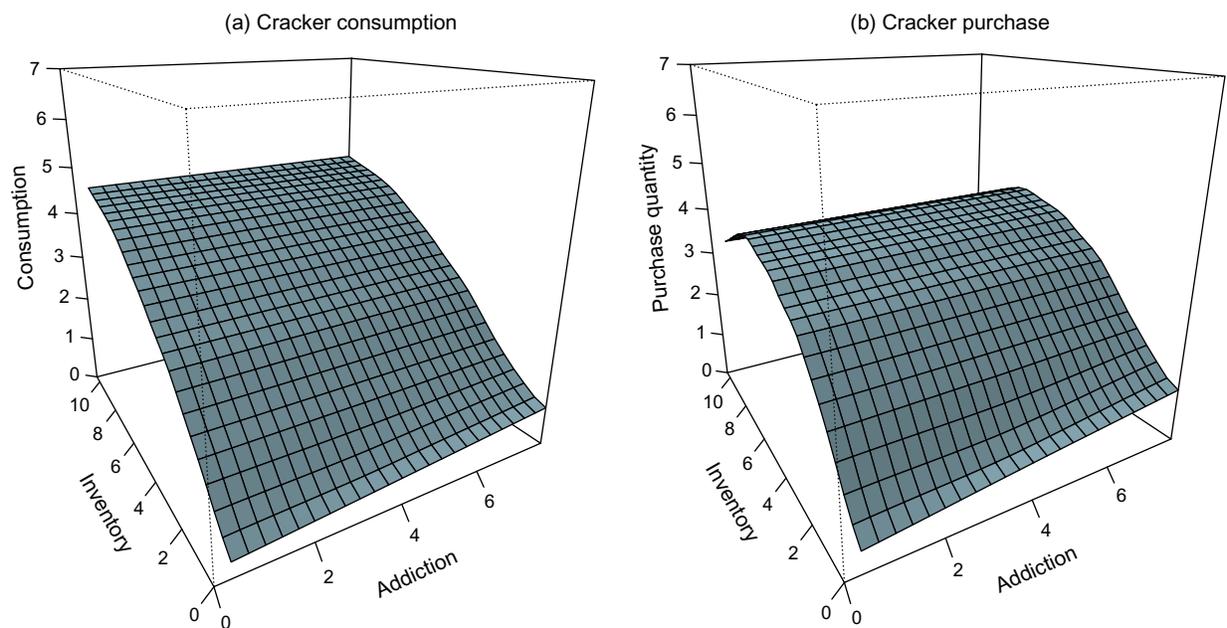


Figure 5 (Color online) Consumption and Purchase Decision Functions for Crackers



category's most expensive products. Second, a 10% category-wide tax. Governments often enact so-called "sin taxes" on addictive substances during rough economic periods. These taxes can play an important role in funding state and federal budgets (*New York Times* 2008, Romm 2009). Third, we eliminate the quantity discounts offered on cartons. The magnitude of this discount varies across tiers, from 8% per pack on low-tier cigarettes to 20% for premium cigarettes. To implement this policy we equalize the price per pack

on all purchase quantities greater than or equal to 10 packs (corresponding to the largest four quantity bins from §2).

To calculate the elasticities, we randomly selected a week near the middle of the sample and implement the policy changes for the rest of the sample. The price processes are re-estimated using the new time series of prices. We re-solve the dynamic programming problem to calculate the new policy functions given the alternative price process and then simulate

the model forward, comparing the new total demand to the baseline demand. All price changes are permanent from the perspective of the consumers. The long-run (arc) elasticities we report compare the total change in demand measured in packs for a specific product (e.g., all premium cigarettes, only cartons of premium cigarettes, etc.) over the entire window.

Table 7 presents the category elasticities under each policy using the full model. First, the category elasticities are about 35% lower in the model without addiction. The magnitude of this discrepancy is roughly consistent across policies, primarily due to the lower price coefficient estimated in model M1. Second, comparing across the columns in the M3 row, the category elasticity is smallest under the premium-tier tax because consumers can substitute to lower tiers at their original prices. The category-wide tax results in more substitution to the outside no-purchase option than under the premium-tier tax.

To further explore these results, Table 8 decomposes the elasticities across tiers and package sizes, reporting a mixture of own- and cross-elasticities depending on the particular policy. The results are separated according to “singles” and “cartons,” defined respectively as purchases of {1, 2–4, 5–9} packs versus 10 packs or more.

Under the premium tax in Table 8, note that the cross-elasticities in the mid- and low-tiers are somewhat small relative to the own-elasticities in the premium tier because the inside choice share is over 80%. Rather than substitute to the outside good, many consumers trade down to less expensive cigarettes. Further evidence of this substitution pattern exists under the category tax, where positive values for the mid- and low-tier single-pack elasticities suggest a net increase in demand for these items. Total demand for these products increases because of substitution from consumers who previously purchased in the premium tier or cartons of the same tier, all of which have negative elasticities.

Interestingly, the category elasticity is also highest under the carton ban as opposed to under the category-wide tax. As expected, single-pack elasticities are largest under the carton ban, yet the carton elasticities in the mid- and lower-tiers are actually lower under a carton ban relative to the category-wide tax. These numbers reflect additional substitution from the premium products to low- and mid-tier cartons, which results in an increase in overall demand.

Table 7 Summary of Category Purchase Elasticities by Policy

Model	Policy		
	Premium tax	Category tax	Carton ban
No addiction (M1)	−0.16	−0.29	−0.33
Addiction (M3)	−0.25	−0.44	−0.56

Given that the premium tier represents about 50% of category sales, such shifts from packs to cartons overwhelms the selection of the no-purchase option.

To help put these results in perspective, we conduct a simple thought experiment to assess the economic importance of the addictive stock. Suppose a consumer with some a_t optimally consumes $c_t(a_t, P)$. Suppose we shock this consumer’s addiction stock by one unit, such that $a'_t = a_t + 1$ with consumption changing to $c_t(a'_t, P)$. What temporary price increase Δ_p would equate the consumption levels, such that $c_t(a_t, P) = c_t(a'_t, P(1 + \Delta_p))$? We are trying to measure the contemporaneous trade-offs between increased addiction, consumption, and prices. We consider a range of addiction levels based on the empirically relevant ranges obtained from estimation. For simplicity and to focus on addiction, we set inventory levels to zero and prices to their average values in Table 1.

Table 9 reports the results. Given this parameterization, the consumption policy function is concave in addiction, such that the relative difference between $c_t(a_t, P)$ and $c_t(a'_t, P)$ is decreasing in a_t . The necessary price changes Δ_p are larger for the light-use segment, despite it being more price sensitive (see Table 6), because this segment experiences greater relative changes in consumption at the lower addiction levels. For the heavy-use segment, relatively small price changes are necessary given that their consumption adjusts very little in response to the shock to their addiction capital. At an addiction level

Table 8 Purchase Elasticity Decomposition by Tier and Package

	Policy		
	Premium tax	Category tax	Carton ban
Premium tier			
Overall	−0.62	−0.52	−0.61
Singles	−0.12	−0.01	0.18
Cartons	−0.67	−0.57	−0.63
Mid tier			
Overall	0.18	−0.40	−0.37
Singles	0.17	0.19	0.35
Cartons	0.19	−0.46	−0.41
Low tier			
Overall	0.18	−0.18	−0.03
Singles	0.16	0.22	0.43
Cartons	0.20	−0.30	−0.17
Category			
Overall	−0.25	−0.44	−0.56
Singles	0.03	0.10	0.24
Cartons	−0.29	−0.51	−0.58

Notes. Purchase elasticities for different policies according to tier and package size. “Singles” are defined as choices of fewer than 10 packs and “Cartons” are defined as choices with 10 packs or more. Note that some elasticities above are cross-elasticities; for example, under the Premium Tax, the results for the mid- and low-tiers and under the Cartons tax, the Singles estimates for all tiers.

Table 9 Quantifying Addiction Capital

Addiction capital	Heavy-use segment (1)			Light-use segment (2)		
	$c_t(a_t, P)$	$c_t(a_t + 1, P)$	Δ_p (%)	$c_t(a_t, P)$	$c_t(a_t + 1, P)$	Δ_p (%)
0				2.43	4.26	65
1				4.26	5.31	29
2	9.13	11.94	47	5.31	6.19	20
3	11.94	12.85	13			
4	12.85	13.40	7			

Notes. Given a level of addiction capital a_t and prices P , reports the baseline level of consumption $c_t(a_t, P)$, the consumption under one unit higher addiction $c_t(a_t + 1, P)$, and the price change Δ_p necessary to equate the consumption levels, $c_t(a_t, P) = c_t(a_t + 1, P(1 + \Delta_p))$. All calculations are done assuming inventory levels are zero and with prices set at their averages.

of $a_t = 2$, the heavy-use segment would require a 47% price change to offset the increased consumption associated with a one unit increase in addiction. For the same addiction level, the light-use segment would only require a 20% price change.

At first glance the required price changes appear somewhat large to offset the effects of the increased addiction. To put these results in perspective, consider the average retail price of cigarettes and subsequent tax changes. According to the Centers for Disease Control and Prevention (CDC), the federal tax on cigarettes has steadily declined as a share of the retail price per pack. In the 1990s and early 2000s, changes in the federal tax rate ranged from about 3% to 6% of the retail price (Orzechowski and Walker 2012). However, in 2007, average retail prices were about \$4.00 and the federal tax of \$0.39 per pack represented less than 10% of the retail price, one of the lowest levels in history. In 2009, President Barack Obama increased the federal taxes by the equivalent of 16% per pack (Lindblom and Boonn 2009). In addition many states have enacted their own sizable taxes in the last two decades. Together these results suggest that policymakers have realized that substantial taxes are justified in order to have a meaningful effect on consumer cigarette purchases.

There are at least two possible concerns with the preceding analysis. First, since banning cartons might induce consumers to make more frequent shopping trips to purchase cigarettes, ideally the model would endogenize the trip decision (as Hartmann and Nair 2010, do in their model of razor and blade purchases). Second, an alternative modeling implementation of the carton ban would be to remove cartons from the choice set. However, this would require changing the model to allow consumers to purchase a large number of single cigarette packs. Rather than rely on our discrete-choice approach to the quantity decision, it might be preferable to directly address the multiple discreteness problem (e.g., see Dubé 2004).

5.4.2. Temporary vs. Permanent Price Changes.

To evaluate how the longevity of the tax affects behavior, we also implement temporary price increases with the premium-tier and compare the results across model specifications and product categories.²⁰

Table 10 reports elasticities for each category estimated under each model. We focus on the results under M3, the full model. For cigarettes, the temporary consumption elasticity is 0.35, about half of the permanent consumption elasticity of 0.63.²¹ The intuition for why the permanent elasticity is greater than the temporary elasticity is that, beyond the initial consumption increase, a permanent price increase produces a long-run decrease in addiction. Permanently lower addiction reduces the benefits of additional consumption. The temporary elasticity of consumption is smaller because addiction is fixed in the short-run.²²

To put our results in perspective, our consumption elasticity estimates are similar to those in earlier studies that report short- and long-run consumption elasticities of about 0.4 and 0.8, respectively (Chaloupka 1991; Becker et al. 1991, 1994). Our finding that permanent consumption elasticities are larger than temporary elasticities is also consistent with theoretical predictions in Becker and Murphy (1988) and Becker et al. (1991). An additional implication of these models is that permanent consumption elasticities are increasing in addiction. More addicted consumers experience a larger change in their future addiction; thus, their long-run consumption is more responsive to a permanent price change. Consistent with this, we find that the permanent consumption elasticities are

²⁰ To implement temporary versus permanent taxes, we assume that consumers are aware of the longevity of the tax when forming their expectations, $\Pi(p' | p)$, as opposed to using $\Pi(p' | p_a)$. Under a temporary tax that moves the price from p to p_a , consumers still form expectations using $\Pi(p' | p)$. Under a permanent price change, consumers use the new price to form expectations according to $\Pi(p' | p_a)$.

²¹ Hendel and Nevo (2006a) compare permanent elasticity estimates from a model with forward-looking consumers to temporary elasticity estimates from a model with static consumers. They find that the static model produces temporary price elasticities that are about 30% higher than the permanent elasticities from the dynamic model. However, the price coefficient in the static model is higher, too. This makes it difficult to assess how much of the different elasticity results are due to forward-looking behavior versus the higher price coefficient.

²² For the sake of comparison, we implement the same taxes for crackers and butter, although such taxes are unlikely to be enacted on these categories. Instead, one could view the taxes as regular price increases. In crackers and butter, no significant difference exists between the elasticity estimates with or without addiction because the parameter estimates in the two specifications are similar. The temporary purchase elasticities of 1.41 and 1.11, respectively, are consistent with prior estimates (Hoch et al. 1995).

Table 10 Purchase and Consumption Elasticities

	Cigarettes			Crackers			Butter		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Consumption									
Temporary	-0.46	-0.28	-0.35	-1.35	-1.21	-1.22	-0.99	-0.90	-0.92
Permanent	-0.31	-0.56	-0.63	-1.24	-1.06	-1.08	-0.81	-0.80	-0.83
Purchase									
Temporary	-0.53	-0.70	-0.84	-1.40	-1.32	-1.37	-1.11	-0.97	-0.99
Permanent	-0.43	-0.56	-0.62	-1.32	-1.26	-1.28	-0.96	-0.85	-0.86

Note. Elasticities calculated using a 10% tax levied on the premium tier.

0.87 for the heavy-use segment compared to 0.53 for the light-use segment.²³

To assess the importance of modeling addiction, we also compare the elasticity estimates from M3 (full model) to M1 (stockpiling only, no addiction). Relative to the full model (M3), the model with stockpiling and no addiction (M1) underestimates the permanent consumption and purchase elasticities by 52% and 35%, respectively. M1 also produces an upward bias of 29% in the temporary consumption elasticity due to changes in other utility parameters: Consumption, utility, and stockout costs increased, while holding costs decreased. The direction of these changes all contribute to a greater incentive to consume.

6. Conclusion

The unique nature of addictive goods necessitates an appropriate model of consumer purchase behavior. Policymakers and firms seek to understand how various interventions affect consumers' decisions to acquire addictive goods ranging from cigarettes to sugary snacks to caffeinated beverages. The extant empirical literature in marketing generally ignores the unique features of addictive goods, despite growing popular interest in moderating the consumption of such products.

This paper uses a dynamic model of addiction and stockpiling to investigate the effects of several policy interventions on cigarette purchases. First, we find that category demand elasticities are about 35% lower when generated using a model that ignores addiction. Second, of the three policies we consider, category

demand is most responsive under a ban on cartons rather than a category-wide tax. Third, a series of simulations using temporary and permanent price cuts show that short-term purchase and consumption elasticities for cigarettes can markedly differ from purchase elasticities.

To assess the model's robustness, we perform a cross-category analysis using two nonaddictive food categories, crackers and butter. The results demonstrate that the model can separately identify stockpiling and addictive patterns in the data. The estimates provide evidence in favor of both patterns in cigarettes and of only stockpiling in crackers and butter, consistent with our intuition about each category.

Our model is subject to several limitations, some of which might represent interesting avenues for future research. The Becker-Murphy model assumes that consumers are forward-looking with time-consistent preferences and complete information about their decisions. Each of these elements of our model can be questioned; smoking addiction may be the result of myopic, time-inconsistent, and irrational behavior. We discuss each element in turn.

First, although some evidence supports forward-looking behavior in smokers (Gruber and Koszegi 2001, Arcidiacono et al. 2007), it is difficult for our model to empirically distinguish between myopic and forward-looking consumers. A myopic model of addiction could be used to fit the purchase data, too. This difficulty is not specific to our paper. Rust (1994) proved the generic nonidentification of the discount factor in dynamic discrete choice models. We prefer to model consumers as forward-looking because their price expectations can properly adjust in the counterfactual simulations, while also maintaining conceptual consistency with the Becker and Murphy (1988) model.

Second, compared with forward-looking behavior, evidence in support of time-consistent preferences is weaker (for a review see O'Donoghue and Rabin 1999). Gruber and Koszegi (2001) present a model of addictive behavior with time-inconsistent preferences and show that it has different normative policy implications compared to the model in Becker

²³ However, a consumer's ability in our model to stockpile creates one distinction between our results and the literature's implications. Table 10 also shows that the temporary purchase elasticities are less than the permanent purchase elasticities. This is the converse of the consumption elasticities. The temporary purchase response is greater because of the incentive to stockpile to avoid stockouts. Stockpiling allows the model to rationalize a short-run increase in demand due to a price cut without ascribing all of the variation to increased consumption or price sensitivity. Note that in the long run, a consumer's consumption and purchase quantities must be equal. Otherwise, inventory will grow without bound.

and Murphy (1988). Machado and Sinha (2007) use a time-inconsistent model to analytically explore the smoking cessation decision. Neither paper, however, structurally estimates their model's parameters. The empirical identification of time-inconsistent preferences in dynamic discrete choice models is the subject of recent work by Fang and Wang (2013). Future research along these lines in the context of addictive goods would be valuable.

Third, the model assumes that consumers have complete information about the addictiveness of the good and that addiction evolves deterministically. This information makes it possible for a consumer to perfectly forecast how current consumption will affect future addiction and subsequent decisions. Under these conditions a consumer cannot be "tricked" into becoming addicted. In reality, some consumers make less than fully-informed decisions about smoking because they are unaware of the negative health consequences, they may not believe them or they may systematically underestimate nicotine's effects on their future decisions. For example, a consumer with low addiction who underestimates the effects of consumption on addiction will probably overconsume today. This consumer's purchase quantity would be less responsive to a price increase, and consequently our model would overestimate the purchase elasticity. If prices were to increase, the same consumers' purchase quantity would be less responsive, and our model would overestimate the purchase elasticity. Future research could attempt to relax this strict informational assumption to create heterogeneity across consumers in their propensity toward addiction.²⁴

These informational limitations are particularly relevant for young people, who are likely to have limited information about smoking risks, addiction, and their own preferences. They might make decisions using shorter time horizons and choose to ignore the long-term consequences of smoking. Some teenagers start smoking as "a symbolic act of rebellion or maturity" (Jarvis 2004, p. 279). By age 20, 80% of smokers regret having ever started (Jarvis 2004). These facts are difficult to reconcile with the current rational addiction framework. Suranovic et al. (1999) present a boundedly rational version of the Becker-Murphy model to help explain several behaviors associated with cigarette addiction over an individual's life. Such work that departs from the fully rational addiction

model could serve as a useful basis to empirically investigate smoking in young people.

Fourth, our model assumes a particular form for the addiction process (Equation (3)). Although this approach is consistent with prior literature, alternative behavioral mechanisms could produce observationally equivalent purchase behavior. For example, a consumer learning about her category preferences might increase consumption over time if she learns to enjoy the category. Empirically distinguishing between these alternative models of positive persistence would be challenging. Ideally, one could obtain data on purchase, consumption, and exposure to various advertising instruments to help disentangle the long-run effects of marketing activities in addictive categories (Bronnenberg et al. 2008).

Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/mksc.2014.0885>.

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²⁴Orphanides and Zervos (1995) present a theoretical model of rational addiction along these lines. Some consumers are not fully informed about the addictiveness of a product and their own tendency to become addicted. These consumers initially underestimate their addictive tendency and are more likely to get "hooked." However, another segment of consumers who know their true addictive tendency never become addicted.

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