Reducing Consumer Inertia in Tobacco Markets *

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December 18, 2023
LATEST VERSION

Abstract

We study the equilibrium effects of tobacco control policies. While tobacco regulation often targets consumers, understanding firms' responses is essential for accurately evaluating the impact of these policies on consumption. We highlight that consumers' dependence on cigarettes, which we refer to as *consumer inertia*, introduces dynamic incentives for firms. Thus, we develop a dynamic oligopoly model and estimate it using product-level data and a panel of smokers. Leveraging large tax fluctuations and a policy that forced approximately 40% of products out of the market, we show that consumers face significant addiction and brand loyalty. We use these estimated preferences to demonstrate the importance of considering firms' dynamic incentives to explain their observed behavior. Lastly, we propose a tractable equilibrium notion to compute market outcomes. We use this framework to examine the counterfactual effect of uniform packaging restrictions and caps on nicotine concentration. We show that firms' responses tend to reinforce the direct effect of these policies. Supply responses strengthen the direct effect because companies' incentives to attract new consumers decrease, since retaining them in the future becomes harder. These dynamic incentives reverse firms' short-term considerations. For example, firms can amplify the impact of uniform packaging even though demand elasticity increases by up to three times and the expected number of products expands by as much as 30%.

*First Version: October 2023. We are grateful to David Besanko, Vivek Bhattacharya, Igal Hendel, Gastón Illanes, Rob Porter, Mar Reguant, and Bill Rogerson for many detailed comments and discussions. We also thank Felipe Berruti, Nick Buchholz, Sebastian Fleitas, Eilidh Geddes, Alexander MacKay, Matt O'Keefe, Anran Li, Jose Salas, Molly Schnell, David Stillerman, Patricia Triunfo, Maren Vairo, Benjamin Vatter, Jingyuan Wang, Tomas Wilner, Hans Zhu, and seminar participants at the IO Graduate Students Seminar at Northwestern for helpful comments. We thank Soledad Fernandez, Gonzalo Chiappara, and the Scanntech team for generously sharing the data.

†I'm deeply grateful to my advisors Igal Hendel, Vivek Bhattacharya, Gastón Illanes and Mar Reguant for their constant guidance and support.

1 Introduction

Tobacco kills 8 million people every year. Although governments have discouraged its consumption through taxation and regulation for decades, the industry remains resilient. Authorities are now considering a new generation of innovative policies to combat the tobacco epidemic. In 2022, for instance, the Food and Drug Administration (FDA) proposed a plan to develop a product standard that would establish a maximum nicotine level to reduce the addictiveness of cigarettes [FDA, 2022]. In addition, several countries have started implementing uniform packaging to reduce the appeal of cigarettes [WHO, 2022].[1] Whereas this type of regulation aims to affect consumer behavior, understanding how tobacco companies will respond is crucial for anticipating the overall impact of these policies on consumption. Echoing this concern, a UK government review highlighted a primary argument against uniform packaging: its potential to "reduce brand loyalty, causing smokers to switch to cheaper brands and encouraging price competition between manufacturers" [Chantler, 2014, pp. 5].

This paper studies the equilibrium effect of tobacco control policies. In particular, we study whether firms' responses amplify or undo the direct impact of regulation on consumers. We stress that smokers' dependence on cigarettes makes the problem of the firm inherently dynamic. Smokers face two well-known sources of inertia. They become *addicted* to tobacco due to nicotine intake and develop persistent *brand loyalty* to the products they smoke [Dawes, 2014]. The industrial organization literature has established that consumer inertia introduces dynamic incentives for firms. Under inertia, future consumption becomes a function of current purchases. This intertemporal link induces firms to consider the long-term implications of their decisions, which modifies how they price and offer products. Klemperer [1987a] found that given consumer inertia, companies would be willing to lower prices to attract a larger customer base and then raise them to profit from the locked-in consumers. Also, the profit sacrifice required to lure customers to a new product can deter their introduction. Since Bain [1956]'s seminal work, economists have identified consumer inertia as a major barrier to entry. Although these theoretical results characterize tobacco companies' incentives to modify their price and portfolios in response to regulation, the equilibrium effects remain an empirical question [Farrell and Shapiro, 1988, Dubé et al., 2009].

To empirically assess the equilibrium effects of regulation in tobacco markets, we develop and estimate a dynamic competition model that accounts for consumers' and firms' responses. Consumers exhibit addiction and brand loyalty, while forward-looking firms choose prices and product portfolios. We then leverage rich variation in the Uruguayan tobacco market to identify and estimate addiction and brand loyalty. In addition, we provide robust empirical evidence that a dynamic competition model is necessary to capture firm behavior realistically. Finally, we propose a computationally tractable equilibrium concept that circumvents the curse of dimensionality and enables the empirical analysis of equilibrium effects.

We use this framework to simulate the equilibrium effect of uniform packaging and nicotine caps, and study the interaction of these measures with taxation. Our results indicate that firms' responses tend to *reinforce*

[1] Australia was the first country to pass plain packaging legislation in 2012. Since then, France (2017), United Kingdom (2017), New Zealand (2018), Norway (2018), Ireland (2018), Hungry (2019), Thailand (2019), Uruguay (2019), Saudi Arabia (2020), Slovenia (2020), Turkey (2020), Belgium (2021), Canada (2022), Singapore (2020), Israel (2020), Netherlands (2021), and Denmark (2022) have enacted some form of plain packaging policy.

the direct effect of these policies on consumers. In the case of uniform packaging, although it can increase competition and favor new entry, it reduces firms' incentives to attract new consumers because companies cannot retain them in the future. Ultimately, we show that once we account for firms' dynamic incentives, uniform packaging is unlikely to backfire due to firms' responses. Similarly, we find that firms' responses *increase* the efficacy of lowering addiction. Firms recognize that because addiction has decreased, they cannot lock customers into their products. Therefore, the policy discourages firms from investing in turning individuals into smokers. This change in strategy induces further decreases in smoking rates. Our results demonstrate that considering firms' responses, particularly their dynamic incentives, is crucial in assessing the policies' impact on consumption. We suggest that discouraging firms from capturing new consumers by restricting their ability to retain them in the future is an effective tool to curb tobacco consumption.

Next, we describe each step of our analysis in detail. Our first contribution is to account for the rich interaction between firm strategies and consumer inertia. We model industry dynamics in a discrete-time, infinite-horizon setting in the spirit of Besanko et al. [2014]. Firms compete by choosing prices and product portfolios. We model demand using a differentiated product specification [Berry et al., 1995], which includes dynamic elements of consumer choice such as addiction and brand loyalty. Our model has two innovations relative to the previous literature. First, it combines entry and exit decisions with consumer inertia in an infinite-period model, allowing for a complex interplay between prices and industry dynamics. Second, our equilibrium notion renders our model suitable for empirical analysis. We propose a tractable equilibrium definition that builds on Fershtman and Pakes [2012] and Ifrach and Weintraub [2017]. It restricts firms' information to their own states and some aggregate market moments instead of tracking all payoff-relevant variables. Our equilibrium is easy to compute, allowing us to solve the model for several levels of addiction and brand loyalty levels, which goes beyond traditional comparisons between the baseline and no-inertia scenarios.

We combine product-level data and a panel of smokers with rich variation from the Uruguayan tobacco industry to identify and estimate the model's primitives. First, we document persistent consumption choices. On average, less than 12% of smokers quit in a year, and more than 80% of smokers repeat the same product choice. Persistent choices reflect both inherent preferences and state-dependent utility influenced by previous behavior, which we refer to as consumer inertia [Heckman, 1981]. Differentiating between inertia and persistent preferences is relevant to firm behavior. Under consumer inertia, past purchases shape future demand, which guides firms' pricing strategies; persistent preferences, in contrast, limit firms' influence on future choices.

The Uruguayan experience provides significant variation in prices and choice sets, which considerably affects smoking rates and helps to identify consumer inertia (addiction and loyalty) separately from persistent preferences. We leverage two primary sources of variation to separately identify inertia and persistent preferences. First, there are notable tax oscillations. These fluctuations arise from (1) governmental priority shifts regarding tobacco control and (2) setting specific taxes at nominal values. Tax-driven price swings aid in studying quitting behavior across tax rates to learn about addiction, following the intuition of Pakes et al. [2021]. Second, a regulation forbade firms from offering multiple products under the same brand name, and the policy forced approximately 40% of products out of the market. For example, Philip Morris discontinued Marlboro sub-varieties, which represented over 25% of total sales. Hence, the choices of customers who "lost" their products help identify the preferences of consumers who are not attached to any particular product but still face addiction, similarly to Handel [2013]. The policy also triggered substantial, transitory relative price changes following product reintroduction, which aids in the study of consumer loyalty [Dubé et al., 2010].

Estimates suggest a high degree of consumer inertia. Current smokers are willing to pay nearly two times the observed average price for any cigarette and more than three times the average price to repeat their product choice. In this regard, the mean own-price elasticity is around -0.9, which implies that firms price in the inelastic region of the demand curve. These estimates are low compared with other industries but consistent with the scarce literature that treats cigarettes as differentiated products [Ciliberto and Kuminoff, 2010, Liu et al., 2015]. Finally, the implied aggregate market elasticity is close to 0.4, in line with a large body of work in the health literature and recent estimates in the Uruguayan market.

We estimate fixed and marginal costs using the method of simulated moments (MSM).[2] Although our equilibrium notion renders MSM computationally feasible, we must overcome a few hurdles. First, we discuss how to address potential equilibrium multiplicity using the absorbing steady state of the game without product assortment. We then observe that prices depend on fixed costs through the next period's portfolio probabilities. Thus, we cannot split the problem into two steps by recovering marginal costs from static first-order price conditions and then solving the entry/exit dynamic game to estimate fixed costs, as in Igami [2017], Igami and Uetake [2020] and Elliott [2022]. However, participation choices and prices define *distinct* combinations of marginal cost and continuation probabilities that could rationalize them. Therefore, conduct still aids identification. Our results show that estimated production costs are small, which implies that taxes represent more than 90 % of firms' total marginal costs. Following Besanko et al. [2010], we define marginal virtual costs as follows: From marginal costs, we subtract the value that acquiring a new customer adds to a company's profits over time. In simple terms, marginal virtual costs represent the cost to serve an additional customer net of how much the customer will contribute to profits in the future. In our setting, customers' long-term value substantially decreases the virtual cost of cigarettes. Interestingly, while products share similar marginal costs due to the high tax incidence, virtual costs vary widely.

Next, we argue that a dynamic oligopoly model under inertia is needed to capture firm behavior realistically. The fact that firms are pricing in the inelastic region of the demand curve already suggests that a static model of competition would not be able to capture firm behavior accurately. Our model explains two market features that would be hard to capture if firms did not account for inertia. First, it explains why firms set low markups despite highly inelastic demand. Demand elasticity, determined empirically by the demand response to prices, can arise from either consumers' low disutility from prices or high inertia. If firms believed consumers' mild response to prices was not due to consumer inertia or were myopic, they would have set prices much higher than observed. We reach the same conclusion even if we assume firms do not face any pre-tax costs. If consumers are unresponsive because they are inert, they also provide a long-term value for the firm. Customers' long-term value, in turn, decreases the virtual cost of selling cigarettes,

[2]Our approach applies to cases where standard solution-free methods are not feasible [Bajari et al., 2007], a situation we encounter as firms operate nationally.

and firms are not compelled to raise prices as much. Second, under the estimated levels of inertia, the model generates significant price discounts when introducing a new product. We observe that predicted and observed introductory pricing strategies—which occasionally implied setting prices at cost for months—are similar and not caused by cost changes or consumer preferences.[3]

Moving to the counterfactual analysis, we first establish the effect of uniform packaging. In our model, we implement this counterfactual policy by reducing the degree of brand loyalty, following the arguments used by the tobacco industry during the implementation of this policy in the UK [Chantler, 2014]. We could think of this analysis as a worst-case scenario for the impact of uniform packaging, since there is evidence that plain packaging makes health warnings more salient [Harris et al., 2018], potentially increasing the likelihood of quitting and reducing smoking initiation. The direct effect of this policy causes consumers to be more price-sensitive and less likely to repeat their choices without lowering their overall cigarette valuation. This direct effect triggers two equilibrium responses that would lead to higher consumption. First, demand becomes more elastic: When we completely eliminate brand loyalty, the elasticity is three times higher, going from around 1 to 3. If firms were myopic, this would lead to substantially lower prices. In addition, reducing brand loyalty lowers barriers to entry, since smaller products can steal buyers from their rivals at a lower cost. According to our estimates, this leads to an increase of around 30% in the expected number of products when we eliminate loyalty. Despite these effects, we observe a meager increase in consumption if loyalty reductions are small and even a decrease for more significant drops. The reason is that firms cannot keep customers captive as efficiently as they could before loyalty declined. Thus, they lack incentives to lower prices to lock customers in. We estimate that this effect is equivalent to increasing firms' costs by a factor of 3.5 when we eliminate loyalty. This rise in *virtual* costs largely offsets and even reverses the increased demand elasticity and product variety.

We then examine the expected effect of nicotine caps, as proposed by the FDA. We implement this counterfactual by reducing the degree of addictiveness from our baseline estimates. The direct effect on consumers is substantial because smoking in the past would not make smoking today any more enjoyable for consumers. Therefore, if firms continue to use the same strategies as in the pre-policy period, eliminating addiction leads to an approximately 30% reduction in smoking rates. Firms' responses reinforce this effect. As policies lower addictiveness, they reduce the long-term value a smoker has for the firm because lower addiction levels increase the probability that consumers will switch to the outside option (quitting). Firms are thus less aggressive in rebuilding their lost customer base, which further lowers consumption. Concretely, firms' strategy adjustment reduces smoking rates 25% more than we would have observed in a counterfactual long-run steady state in which firms did not adjust their strategies.

Finally, we study the interaction between these policies and taxation. We argue that plain packaging and nicotine caps can help governments achieve target smoking rates without increasing the burden on consumers as much. Regulators often aim to discourage the consumption of "sin goods" such as tobacco, alcohol, and sugar by making them less affordable. However, evidence suggests that this approach has neg-

[3] To make sure that other mechanisms do not drive the changes, we force product-specific costs to be constant over time. Our approach is reminiscent of Benkard [2004], which estimates all primitives of the model without ever solving the equilibrium. Although we use the equilibrium computation to estimate firms' costs, we do so in a way that does not fully rationalize the data, letting us test the model's predictive power.

ative distributional consequences, as recently illustrated by Conlon et al. [2022]. Significant reductions of inertia (through our counterfactual policies) can achieve the joint effect of lowering the cost for smokers *and* reducing smoking rates. Ultimately, our results demonstrate that limiting firms' ability to retain customers in the future–which can take many forms, such as reducing addiction, inducing more competition, or adding regulatory uncertainty–can be a valuable tool to limit consumption. Moreover, our framework can be used to study the effect of policies in other markets where consumer inertia is significant, such as gambling, or in other markets with high switching costs.

Related Literature We build on three strands of the literature. First, our paper contributes to the literature on tobacco control. While many studies have investigated the effect of multiple policies to reduce tobacco consumption, ours is one of the few studies accounting for firm responses and industry dynamics. See [Levy et al., 2019] for an in-depth discussion about tobacco control from an economic and marketing perspective. A few exceptions are Ciliberto and Kuminoff [2010], evaluating the effect of the 1997 Master Settlement Agreement (MSA) on firms' ability to collude, and Qi [2013]'s study about industry dynamics following the 1971 cigarette advertising ban in the United States. Our work also relates to Barahona et al. [2020], which accounts for firms' responses to evaluate the equilibrium effect of food labeling policies, and Abi-Rafeh et al. [2023], which account for firms' dynamic incentives to study the effect of sin taxes and advertisement restrictions in the sugar-sweetened beverage industry.

Our paper also advances the understanding of industry dynamics under consumer inertia. We build on the modern research on dynamic price competition in this context [Dubé et al., 2009, Arie and E. Grieco, 2014, Fabra and García, 2015], and introduce entry and exit considerations following the framework laid out by Benkard [2004], Farrell and Katz [2005], Besanko et al. [2014, 2019], Sweeting et al. [2020] to study games of dynamic competition under learning-by-doing, network externalities, and limit-pricing. This approach allows us to highlight additional implications of the investing-and-harvesting tradeoff.

Our results capture Bain [1956]'s intuition of brand loyalty as a barrier to entry and are in the same spirit as Fleitas [2017]'s findings. These results differ from the few papers exploring the relationship between inertia and participation choices in simple theoretical frameworks [Farrell and Shapiro, 1988, Beggs and Klemperer, 1992, Gabszewicz et al., 1992], suggesting that higher inertia would facilitate entry due to increased industry profits. Likewise, we find that under our baseline estimates, firms do not have incentives to induce rivals' exit or deter entry. Evaluating this possibility is particularly relevant since there were actual predation allegations during our study period, and our competition model can endogenously create incentives to predate [Klemperer, 1987b, Fumagalli and Motta, 2013].[4] According to our estimates, firms' incentives to capture new consumers were sufficiently strong to generate the aggressive discounts observed in the data, providing evidence against anticompetitive behavior. We also find a non-monotonic relationship between prices and brand loyalty. This relation appears to be a robust feature of competition under inertia and aligns with most of the literature [Dubé et al., 2009, Arie and E. Grieco, 2014, Fabra and García, 2015]. Our work suggests this pattern remains even after introducing entry and exit decisions.

[4]Philip Morris was sued for predatory pricing due to its aggressive pricing strategy, following the policy that eliminated multiple products.

Third, we contribute to expanding the empirical tools available to analyze dynamic oligopolies. Our approach constructs an empirically tractable equilibrium notion that relies on limiting firms' information as in Fershtman and Pakes [2012], and leverage Ifrach and Weintraub [2017]'s moment-based Markov Equilibrium intuition to circumvent the issues created by the introduction of persistent asymmetric information. Our approach relates to several recent papers that use similar computationally tractable equilibrium notions, such as Jeon [2022], Gowrisankaran et al. [2022]. While building on Ifrach and Weintraub [2017], our equilibrium accommodates interactions between dynamic controls and rivals' states, inherent to competition under inertia. In this setting, firms are strategic about the effect that their own dynamic controls (prices and products) have in the evolution of the aggregate industry moments (sum of rivals' market shares), even if their own state is insignificant. Still, we reduce the dimensionality of the problem by restricting firms' ability to monitor what rivals' customer bases are. Instead, firms infer individual products lagged market shares using the long-run distribution of shares over the recurrent class, conditional on the information they hold.

We also use polynomial approximation to reduce the computational burden of solving the model, an approach previously used to solve dynamic oligopoly models by Doraszelski [2003], Sweeting [2013], Fowlie et al. [2016]. Finally, we show how to use the solution of the model to estimate firms' primitives. While there is an increasing number of studies characterizing, identifying, and evaluating consumer inertia through a variety of methods [Dubé et al., 2010, Handel, 2013, Shcherbakov, 2016, Illanes, 2017, Luco, 2019, Pakes et al., 2021, Kong et al., 2022], the literature on estimating firms' costs in such contexts remains limited. The recent empirical work on price competition under inertia generally takes firms' costs as given [Dubé et al., 2009, MacKay and Remer, 2021] or uses solution-free approaches to estimate them [Fleitas, 2017].

2 A dynamic model of competition under inertia

We first analyze firms' equilibrium behavior focusing on a pure strategy Markov perfect equilibria [Maskin and Tirole, 1988]. Here, we introduce the main elements of our dynamic model. To simplify notation, we assume firms produce one product. We extend the model to multi-product firms in Appendix A.2. In the general model, a fixed number of firms make portfolio and pricing decisions. In Section 2.2, we modify firms' information and define the equilibrium in that context.

Firms & Time Horizon The industry evolves over discrete time in an infinite horizon. We denote each period by $t \in \mathbb{N}$. There are F firms. Firm f decides whether to offer its product (which we also denote by f) at period t and sets its price. Consumers' choice set at t is $\mathbb{J}_t \in \{0,1\}^F$, with $\mathbb{J}_{ft} = 1$ if product f is offered at t. We call the set of all possible choice sets $\mathscr{J}$, of dimension 2^F.

Demand Demand is based on the differentiated product discrete choice model but also incorporates dynamic elements of consumer choice. In particular, we allow for habit formation in smoking (addiction) [Ciliberto and Kuminoff, 2010] and product loyalty [Dubé et al., 2010].

Consumer i in market m at period t chooses a single product or the outside option–not to smoke. We add endogenous, time-varying, individual preferences to the usual logit model. Concretely, utility depends on the state $z \in \{1,...,N\}$, i.e., the product they patronize, or $z = 0$ if they have no affiliation.

Consumer i's utility from consuming product j in market t, if she was in state z, is

$$\begin{aligned} u_{ijt}(z,\mu^D) &= \delta_t + \delta_j + \sum_r \sum_k (D_i^r X_j^k)\gamma^{kr} + \eta_0 1\{z \neq 0\} + \eta_1\{z = j\} + \varepsilon_{ijt} \quad \text{if } j \neq 0 \\ u_{i0t}(z,\mu^D) &= \varepsilon_{i0t} \quad \text{otherwise} \end{aligned} \tag{1}$$

δ_t is the mean valuation for cigarettes in period t, δ_j is product j's mean utility.[5] $\sum_r \sum_k (D_i^r X_j^k)$ represents the individual-specific static component of utility: X_j^k are observable product characteristics, and D_i^r denotes demographic variables. Consumer demographics define N consumer types.

Furthermore, consumers' utility is state-dependent. First, individuals get extra utility η_0 (if positive) from consuming any inside goods if they were previously affiliated with any product. We coin this term "addiction" since it makes consumers more likely to choose an inside good if they previously consumed any cigarette. Finally, η_1 indicates that individuals get higher utility (if $\eta_1 > 0$) from the good they are affiliated to than from any other, and we denote it "product loyalty". Our main specification does not add individual-specific, time-invariant valuations for each product.[6] μ^D summarizes all consumer preferences: $\mu^D = (\delta_t, \delta_j, \gamma^{kr}, \eta_0, \eta_1)$. Finally, ε_{ijtm} is a type I extreme value error term.

Under these assumptions, today's choices depend on the previous period's decisions. Thus, demand at t is a function of product characteristics, prices, and lagged market shares $S_{t-1} \in [0,1]^{F \times N}$ for every product-consumer type, taking into consideration the available choice set, $\mathbb{J}_t$.

$$D_{ft} = D_{ft}(p_t, S_{t-1}, \mathbb{J}_t; \mu^D) = M \times S_{ft}(p_t, S_{t-1}, \mathbb{J}_t; \mu^D) \tag{2}$$

where M is the market size, fixed throughout time.

Variable Profits Prices, demand, and marginal production costs (c_{ft}) determine per-period profits.

$$\pi_f(p_t, S_{t-1}, \mathbb{J}_t, c_{ft}, \mu^D) = (p_{ft} - c_{ft}) D_{ft}(p_t, S_{t-1}, \mathbb{J}_t; \mu^D) \tag{3}$$

[5] In demand estimation, we allow product-specific mean utilities to vary across markets (time and stores) and time. However, we assume firms aggregate the distribution of shares at the national level and assume product valuations do not change over time. We then decompose the product-store-specific time-varying mean valuation into a time-varying component δ_t, a product-specific, time-invariant component δ_j, and a market δ_m component. While this assumption is used for computational tractability of the equilibrium, we believe the product-specific, time-varying mean valuations are designed to fit econometric models to data. Therefore, we see our assumption not so much as a shortcoming of the model but rather as a way to approximate firms' beliefs more realistically. More precisely, the decomposition from demand estimation to primitives used in the model is $\delta_{jmt} = \delta_m + \delta_t + \delta_j + \varepsilon_{jmt}$. Aggregating from store-level demand to national demand requires additional adjustments to ensure that the market shares and elasticity are consistent with the data.

[6] There are two important notes in this regard. First, the variation in our data is rich enough to identify flexible specifications of unobserved persistent preferences. Second, although it would be hard to solve for the MPE of the supply side model once we allow for individual-specific, time-invariant valuations, the equilibrium definition we propose in Section 2.2 can flexibly handle it.

We assume that all firms' marginal costs c_{ft} are public information. We decompose products' marginal costs into a time-invariant, product-specific component and a time-varying term common to all products. Thus, we can write marginal costs as $c_{ft} = c_t + c_f$. This assumption makes particular sense in the tobacco industry: the marginal cost of producing a cigarette is well-known, stable, and largely homogeneous across firms.

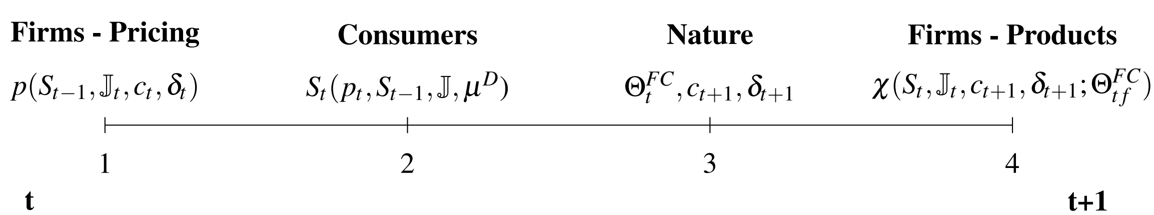
Fixed Costs Each period, firms decide whether to offer their products. We assume firms are established in the market and do not need to pay entry costs to provide new products. They only need to pay a fixed cost Θ_f^{FC} to keep their products in the market. This assumption is sensible since it is relatively easy for established firms to introduce and sell new products if they are profitable. Even outsiders to the tobacco industry can import international brands to distribute them nationally.

Fixed costs are private information, i.i.d realizations across products and time, from distribution F_{FC}. Fixed costs are the only source of firms' private information. That is, all firms know each other's marginal costs and the distribution of fixed costs but not the specific realizations of the latter. Moreover, let $\chi_{ft} \in \{0,1\}$ denote product f's participation choice, where a value of 1 indicates that the product will be offered at period $t+1$. The assumption of private information of fixed costs is usual in the literature to ensure that an equilibrium exists. In our case, although it does not guarantee existence, it provides tractability.

Timing of Events The timing of the stage game is as follows

1. At the beginning of the period, all firms observe past market shares (current customer base), the product portfolio, production costs, and consumer preferences. Then, they set prices to compete in the product market.
2. Market shares realize.
3. Costs and consumer preferences update, and firms privately draw fixed cost shocks.
4. Firms make portfolio decisions and pay fixed costs accordingly. New products enter the market with zero market share.

Figure 1: Stage Timeline



Transition Dynamics Today's prices, past market shares, and the current choice set determine the next period's customer base. That is,

$$S_{ft} = \begin{cases} S_f(p_t, S_{t-1}, \mathbb{J}_t; \mu^D) & \text{if } \mathbb{J}_{jt} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Equivalently, participation choices fully determine the next period's industry structure. Because firms' fixed costs are private information, entry and exit decisions are random variables from the perspective of the rivals. Thus, firms only need to know rivals' participation probabilities when forming an expectation over future states. We call participation probabilities $\phi_f \in [0,1]$. Finally, marginal costs and consumer preferences follow an exogenous transition, that is, $dF(c_{t+1}|s, \mathbb{J}_t, c_t, p_t, \chi_t) = dF(c_{t+1}|c_t)$, $dF(\delta_{t+1}|s, \mathbb{J}_t, c_t, p_t, \chi_t) = dF(\delta_{t+1}|\delta_t)$. Note that δ_t is the only component of μ^D that varies throughout time.

State Space All payoff relevant variables are past market shares (by consumer type), industry structure, marginal costs, and consumer preferences. Although firms observe the private information shocks before making participation choices, we show how to integrate them to keep the state space equivalent to a game of complete information. Thus, let the commonly observed vector of state variables be $\mathbb{X}_t$. This is defined as $\mathbb{X}_t = (S_{t-1}, \mathbb{J}_t, c_t, \delta_t)$, where $S_{t-1} \in [0,1]^{F \times N}$, $c_t \in \mathbb{R}$, $\delta_t \in \mathbb{R}$, and $\mathbb{J}_t \in \{0,1\}^F$.[7]

Firms Objective and Choices Firms set prices and make portfolio decisions to maximize expected discounted profits.

$$V_f(S_{t-1}, \mathbb{J}_t, c_t, \delta_t) = \max_{p_f, \chi_f} \mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \left\{\pi_f(p_\tau, S_{\tau-1}, \mathbb{J}_\tau, c_\tau, \delta_\tau) - \chi_{f\tau}\Theta_f\right\} | \mathbb{X}_t, \Theta_f\right] \tag{5}$$

where the expectation is taken over current firms' participation actions, future values of the actions, private shocks, and state variables.

Markov Strategies In an MPE, firms' behavior depends only on the states and private shocks. A Markov strategy for firm f is a function $\sigma_f : \mathscr{X} \times \mathscr{V}_f \to \mathscr{A}_f$, where $\mathscr{X}$ is the support of the commonly observed states, $\mathscr{V}_f$ is the support of the private shocks of firm f, and $\mathscr{A}_f$ is the support of the actions. A profile of Markov strategies is $\sigma = (\sigma_1, ..., \sigma_N)$ with $\sigma : \mathscr{X} \times \mathscr{V}_1 \times ... \times \mathscr{V}_N \to \mathscr{A}$. Observe that price policies $\sigma_k^p(\mathbb{X})$ do not depend on any private shock, while participation policies do, $\sigma_k^\chi(\mathbb{X}; \Theta_f)$, due to our timing and information assumptions.

A profile of Markov strategies is an MPE if there is no firm f and alternative Markov strategy σ'_f such that firm f prefers playing σ'_f to σ_f when other players play σ_{-f}.

Bellman Equation If firm behavior is given by a Markov strategy profile σ, then we can write firms' expected profits recursively.

[7] Observe that $\mathbb{J}_{jt} = 0$ cannot be interpreted exactly as if lagged shares were 0 since it internalizes that the product is not currently being offered. In contrast, $\mathbb{J}_{jt} = 1, S_{j,t-1} = 0$ indicates that product j does not have a loyal base, but it is available in the market. Nevertheless, it is true that if $\mathbb{J}_{jt} = 0$ then $S_{j,t-1} = 0$ for all j.

At the last stage, when private information costs are realized, the value of the firm under the current period choice set, market shares, costs, and preferences is

$$U_f(S_t, \mathbb{J}_t, c_{t+1}, \delta_{t+1}, \Theta_f|\sigma) = -\sigma_f^{\chi}(S_t, \mathbb{J}_t, c_{t+1}, \delta_{t+1}, \Theta_f)\Theta_f + \beta \int V_f(S_t, \beth, c_{t+1}, \delta_{t+1}|\sigma) dP(\beth|\sigma^{\chi}) \tag{6}$$

where $\beth$ represents a random variable whose elements are possible choice sets, and belong to $\mathscr{J}$.

Then, moving backward to the first stage, firms set prices taking into consideration the state $(S_{t-1}, \mathbb{J}_t, c_t, \delta_t)$ and continuation payoffs before participation choices are taken: integrating $U_f(S_t, \mathbb{J}_t, c_{t+1}, \delta_{t+1}, \Theta_f|\sigma)$ over Θ_f. The value at this point can be written as

$$V_f(S_{t-1}, \mathbb{J}_t, c_t, \delta_t|\sigma) = \pi_f(\sigma^p, S_{t-1}, \mathbb{J}_t, c_t, \delta_t) + \int \left(\int U_f\left(S_t(\sigma^p), \mathbb{J}_t, c_{t+1}, \delta_{t+1}; \Theta_f|\sigma\right) dF(c_{t+1}|c_t) dF(\delta_{t+1}|\delta_t) \right) dF_{\Theta_f} \tag{7}$$

Note, also, that preferences and costs update between the beginning and end of the period.

2.1 Optimal choices

We solve the stage game backward to analyze firms' decisions, from the entry/exit phase to the price-setting stage.

2.1.1 Firms' Participation

Suppose there are only two firms. If a firm participates in the market, its continuation payoff -omitting shares, costs, and preferences- is

$$\beta \left(V_1((1,1))\sigma_2^{\phi} + V_1((1,0))(1-\sigma_2^{\phi}) \right)$$

while if it does not participate, it is

$$\beta \left(V_1((0,1))\sigma_2^{\phi} + V_1((0,0))(1-\sigma_2^{\phi}) \right)$$

Therefore, firm 1 participates in the market if and only if

$$\Theta_1 \leq \beta \left(\sigma_2^{\phi} \left(V_1(1,1) - V_1(0,1) \right) + (1-\sigma_2^{\phi}) \left(V_1(1,0) - V_1(0,0) \right) \right) = \bar{\Theta}_1(\sigma_2^{\phi})$$

More generally, the threshold $\bar{\Theta}_1$ does depend on the states of the game $S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}$. Thus, we can write optimal participation policies as the following cutoff rule

$$\sigma_f^{\chi}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \Theta_f) = \begin{cases} 1 & \text{if } \Theta_f < \bar{\Theta}_f(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \sigma_{-f}^{\phi}) \\ 0 & o/w \end{cases} \tag{8}$$

where the threshold is the difference in expected continuation payoffs between participating in the market or not[8], taking into consideration that other products participate according to rule σ_{-f}^{ϕ}. Therefore, equilibrium participation policies solve the fixed-point problem

$$\sigma_f^{\phi}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}) = F_{\Theta}(\bar{\Theta}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \sigma_{-f}^{\phi}) \quad \forall f \tag{9}$$

Next, observe that representing participation choices by the probability of offering product f is without loss of information. Letting $\mathbb{X}' = (S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1})$, observe that $\sigma_f^{\chi}(\mathbb{X}', \Theta_f) = 1\{\Theta_f \leq \bar{\Theta}_f(\mathbb{X}')\}$, hence $\sigma_f^{\phi}(\mathbb{X}') = \int 1\{x \leq \bar{\Theta}_f(\mathbb{X}')\} dF_{\Theta}(x) = F(\bar{\Theta}_f(\mathbb{X}'))$ and $\bar{\Theta}_f(\mathbb{X}') = F_{\Theta}^{-1}(\sigma_f^{\phi}(\mathbb{X}'))$.[9]

Then, rewriting firm f's problem taking participation probabilities as controls and integrating U_f over realizations of Θ_f we get

$$U_f(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}; \sigma) = -E\left[\Theta_f \times 1\{\Theta_f \leq \bar{\Theta}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \sigma_{-f}^{\phi})\}\right] + \beta E[V(S_t, \beth, c_{t+1}, \delta_{t+1}) | \sigma^{\phi}] \tag{10}$$

where the second expectation is taken over all possible choice sets $\beth$, according to participation probabilities σ^{ϕ} and exogenous distributions.

2.1.2 Firms' Pricing

In the price-setting stage, the Bellman equation of firm f is

$$\begin{aligned} V_f(S_{t-1}, \mathbb{J}_t, c_t, \delta_t | \sigma) = \max_{p_f} \{ \pi_f(p_f, \sigma_{-f}^{p}, S_{t-1}, \mathbb{J}_t, c_t, \delta_t) - \int (E\left[\Theta_f \times 1\{\Theta_f \leq \bar{\Theta}(S_t(p_f, \sigma_{-f}^{p}), \beth, c_{t+1}, \delta_{t+1}, \sigma_{-f}^{\phi})\}\right] + \\ \beta E[V(S_t(p_f, \sigma_{-f}^{p}), \beth, c_{t+1}, \delta_{t+1}) | \sigma^{\phi}] dF(c_{t+1}|c_t)) dF(\delta_{t+1}|\delta_t) \} \end{aligned} \tag{11}$$

Taking derivatives of Equation 11 with respect to p_f, we get FOC for dynamic prices:

$$\frac{\partial \pi_{ft}}{\partial p_{ft}} - \left\{ \frac{\partial E[\Theta_f \sigma_f^{\phi}]}{\partial \sigma_f^{\phi}} \sum_{k:\mathbf{J}_{kt}=1} \frac{\partial \sigma_f^{\phi}}{\partial S_{kt}} \frac{\partial S_{kt}}{\partial p_{ft}} \right\} + \beta \sum_{k:\mathbf{J}_{kt}=1} \frac{\partial EV_f}{\partial S_{kt}} \frac{\partial S_{kt}}{\partial p_{ft}} + \beta \sum_{k:\mathbf{J}_{kt}=1} \sum_{r=1}^{F} \sum_{\beth \in \mathscr{J}} \left(\frac{\partial Pr(\beth|\sigma^{\phi})}{\partial \sigma_r^{\phi}} V_f(\beth) \right) \frac{\partial \sigma_r^{\phi}}{\partial S_{kt}} \frac{\partial S_{kt}}{\partial p_{ft}} = 0$$

[8]In the general case, the threshold is determined by the following equation:

$$\bar{\Theta}_k(\mathbb{X}') = \beta \left\{ E_{\Theta_{-k}}[V_f(S, \beth, c') | \sigma_{-k}^{\chi}(\mathbb{X}'), \mathbb{X}', \beth_k = 1] - E_{\Theta_{-k}}[V_f(S, \beth, c') | \sigma_{-k}^{\chi}(\mathbb{X}'), \mathbb{X}', \beth_k = 0] \right\}$$

[9]In Appendix, A.2, we discuss the assumptions to obtain an equivalent representation for multi-product firms.

Note two facts. First, the second term and the summands on the last term that account for the effect of firms' own probability ($r = f$) cancel out due to firms' participation optimality–an envelope condition. Second, note that $\sum_{\daleth \in \mathscr{J}} \frac{\partial Pr(\daleth|\sigma^{\phi})}{\partial \sigma_r^{\phi}} V_f(\daleth) = E[V_f|\daleth_r = 1] - E[V_f|\daleth_r = 0]$. Therefore, we can simplify the previous equation

$$\frac{\partial \pi_{ft}}{\partial p_{ft}} + \beta \sum_{k:\mathbf{J}_{kt}=1} \left\{ \frac{\partial EV_f}{\partial S_{kt}} + \sum_{r=1,r\neq f}^{F} \left(E[V_f|\daleth_r = 1] - E[V_f|\daleth_r = 0]\right) \frac{\partial \sigma_r^{\phi}}{\partial S_{kt}} \right\} \frac{\partial S_{kt}}{\partial p_{ft}} = 0 \tag{12}$$

It is usually helpful to decompose pricing incentives. For that, we can invert firms' price FOC.

$$p_{ft} = \underbrace{\left(c_f - \frac{\beta}{M}\frac{\partial EV_f}{\partial S_{ft}}\right)}_{\text{Virtual Cost}} - \underbrace{\frac{S_{ft}}{\frac{\partial S_{ft}}{\partial p_{ft}}}}_{\text{Static Markup}} \underbrace{- \sum_{k:\mathbf{J}_{kt}=1,k\neq f} \frac{\frac{\partial S_{kt}}{\partial p_{ft}}}{\frac{\partial S_{ft}}{\partial p_{ft}}} \left(\frac{\beta}{M}\frac{\partial EV_f}{\partial S_k}\right)}_{\text{Dynamic Business Stealing}} + \underbrace{\frac{\beta}{M} \sum_{k:\mathbf{J}_{kt}=1} \left(\sum_{r=1,r\neq f}^{F} \left(E[V_f|\daleth_r = 1] - E[V_f|\daleth_r = 0]\right) \frac{\partial \sigma_r^{\phi}}{\partial S_{kt}}\right) \frac{\frac{\partial S_{kt}}{\partial p_{ft}}}{\frac{\partial S_{ft}}{\partial p_{ft}}}}_{\text{Entry Deterrence/Exit Inducing}} \tag{13}$$

2.1.3 Discussion

The first two terms on the RHS are almost identical to firms' optimal pricing without consumer inertia. The central difference is that firms consider the additional value of a customer to its long-term profits as the negative of a cost. We follow Besanko et al. [2010] and call the difference between the marginal costs and this additional value *virtual costs*. Then, firms markup opportunity costs based on consumers' elasticity. These two terms are the core of the dynamic pricing problem from a quantitative point of view. Additionally, they represent the well-known harvesting and investing motives [Farrell and Klemperer, 2007].

Investing characterizes the incentives to reduce prices to capture new customers for the firm. Equation 13 illustrates that the additional value a customer brings to the long-term value of the firm is equivalent to a reduction on the virtual cost of serving them.[10] Harvesting, on the other hand, is the incentive that firms have to increase prices to extract more value from their current locked-in customer base. Equation 13 also isolates these incentives through the static markup. As firms' locked-in customer base grows and residual demand becomes more inelastic, the markup increases. In this way, we recast the investing-harvesting logic into the usual inverse elasticity pricing rule.

On this point, it is helpful to understand how these incentives change with the size of consumer inertia. In a companion paper, Pareschi [2023] uses simulations to analyze industry dynamics under consumer inertia, with entry and exit. He notes that prices decrease for low inertia levels and then increase, a relationship previously observed by Dubé et al. [2009] and others in settings without participation decisions. As state dependence increases, the long-term value of an additional customer unambiguously increases, and the virtual cost of serving them drops. On the other hand, the effect of inertia on markups is ambiguous. Although locked-in customers are indeed more inelastic, from the firm's perspective, rivals' customers become more

[10] Note that the virtual costs depend on the size of the firm's locked-in customer base, but also on other firms' customer base. A similar intuition is encountered in Hortaçsu et al. [2022], though they refer to virtual costs as opportunity costs.

sensitive to prices. If the latter still represents a relevant part of all customers in the market, higher consumer inertia can even increase demand elasticity–see Appendix A.5 for a formal treatment. Arie and E. Grieco [2014] and Fabra and García [2015] offered a similar intuition as they noted that if the proportion of repeated customers is low, firms decrease prices to compensate new customers for switching. Indeed, Arie and E. Grieco [2014] concludes that firms may set lower prices due to this compensating effect, even if they are not forward-looking.

Third, firms internalize the business stealing effect on all products in the market, even if they do not jointly control them.[11] Firms consider the impact their prices have over all other products in the market because they understand that stealing customers from rivals will trigger a competitive response in the future. While in principle, this effect could create upward or downward pressure on prices, our simulations suggest they usually soften competition.[12] Finally, participation choices introduce a fourth term with no counterpart in the static case. Firms can affect rivals' participation by changing their next-period loyal base. This new mechanism creates incentives to deter rivals' participation by lowering their access to the market. These terms illustrate that in markets with inertia, firms can have incentives to induce exit or prevent entry, which was first noted by Klemperer [1987b] and recently incorporated into a legal theory of predation by Fumagalli and Motta [2013]. Pareschi [2023] suggests that dominant firms are unlikely to engage in meaningful entry-deterrence or exit-inducing behavior. Indeed, he finds that the game is primarily cooperative.

Although participation choices do not have a sizeable quantitative influence on prices, inertia does affect equilibrium participation decisions. In simulations, higher inertia tends to make entry harder. Still, it also increases the value customers have for firms and makes them more reluctant to discontinue well-established products. Hence, its effect on the equilibrium number of products depends on the specific level of inertia, the asymmetry between firms, and the size of fixed costs [Farrell and Shapiro, 1988, Beggs and Klemperer, 1992, Gabszewicz et al., 1992, Fleitas, 2017, Pareschi, 2023].

2.2 Equilibrium Computation

The payoff relevant variables are past market shares (by consumer type), industry structure, time-varying marginal costs, and mean cigarette valuation. In our empirical setting, we assume there are nine distinct product segments.[13] Even if we work with a coarse approximation of the value function, using a few nodes for each product, say 10, the state space would be approximately $11^{(9\times4)}$ plus aggregate costs and common valuations. Neither researchers nor market participants can track this state space for computational reasons. Therefore, we must modify our equilibrium notion to capture market behavior more accurately and make progress in our empirical application. Our approach can be interpreted as a new equilibrium definition in a model of asymmetric information following Fershtman and Pakes [2012]'s Experienced Based Equilibrium (EBE) or as an approximation to the underlying MPE as Ifrach and Weintraub [2017]'s moment-based

[11] We refer to business stealing as how much of the share a firm loses by increasing prices goes to each remaining product

[12] This is contrary to the models of competition with network effects or learning-by-doing, where the business stealing effect usually induces more competition [Farrell and Katz, 2005, Besanko et al., 2010].

[13] These segments aggregate around 25 products, for which firms set uniform prices, make similar entry/exit decisions, and consumers value them similarly. See Section B and Appendix B.2 for a detailed analysis of our aggregation and how to bound the error it introduces into the model.

Markov Equilibrium (MME). We now detail how our procedure works.

First, we assume firms do not closely monitor all payoff-relevant variables. In particular, firms do not know exactly their rivals' customer base size nor the distribution of consumer types within each product customer base. This introduces persistent asymmetric information between the firms. Hence, in addition to payoff-relevant states, agents have informationally relevant ones. In this case, the complete history of past actions and states becomes relevant. To circumvent this challenge, we follow the approach in Ifrach and Weintraub [2017] and assume that firms condition only on some aggregate market moments.

We restrict firms information sets I_f to aggregate shares of products in their own portfolio –not consumer-type specific shares– any other relevant market shares (which might be dominant firms, close competitors, or none of them), and an aggregate state representing the total sales of all products they are not closely monitoring. This aggregate is all the additional information firms use to infer payoff relevant states and rivals' information sets. Although this is an assumption on firms' cognitive abilities, Ifrach and Weintraub [2017] argues it can closely approximate the MPE. Formally, firm f tracks the market shares of T^f products with $\#T^f \leq F$. S^f_{t-1} represents the vector of past market shares of all products that belong to T^f and $\bar{S}^f_{t-1}$ the sum of all past shares of non-tracked products. We call the vector of private information states $z^f_t = (S^f_{t-1}, \bar{S}^f_{t-1})$. In addition, firms have information about whether a product is being offered, the common component of costs, and mean valuations for cigarettes. Thus, $\xi_t = (\mathbb{J}_t, c_t, \delta_t)$ are the public component of information sets I_f. Hence, the information set of firms is $I_f = (z^f_t, \xi_t)$. Strategies are functions from the space information set $\mathscr{I}_f$ to the space of actions (prices and participation decisions): $\tilde{\sigma}_f = \tilde{\sigma}_f(z_t, \xi_t) : \mathscr{I}_f \to [0,1]^{\mathbb{J}_f} \times \mathbb{R}$.

Next, we define firms beliefs about the distribution of payoff relevant states, conditional on the information sets: $pr(\{S_{ijt-1}\}_{i,j}, \mathbb{J}_t, c_t, \delta_t | I_f)$ –from this distribution firms can compute $pr(I_{-f}|I_f)$ too. Firms' beliefs about consumer types conditional on their previous consumption choices are drawn from the observed distribution in the data. This allows firms to construct market shares without knowing how many consumers of type i patronized product k in the previous period. Although this is an assumption about firms' behavior, it is consistent with equilibrium plays. See Appendix A.1 for details.

Then, we leverage the stationary distribution of market shares over the recurrent class of the game without entry and exit to construct firms' beliefs about non-tracked payoff relevant states conditional on their information set. In particular, for any specific choice set $\mathbb{J}$, we can compute the distribution of rival states conditional on (z^f_t, c_t, δ_t). Equipped with these beliefs, we can calculate the expected demand for each strategy profile, which is enough to determine expected profits and information set transitions.

$$S^e(z^f_t, \xi_t; \tilde{\sigma}) = E\left[S(\{S_{ijt-1}\}, \mathbb{J}_t, c_t, \delta_t; \tilde{\sigma}_f, \tilde{\sigma}_{-f}(I_{-f})) | I_f; \tilde{\sigma}\right] \tag{14}$$

Furthermore, we can redefine the value function. When firm f plays strategy $\tilde{\sigma}'_f$ and rivals follow strategies $\tilde{\sigma}_{-f}$, the value of firm f is,

$$\tilde{V}_f(I_f|\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) = \pi^{e(f)}(I_f;\tilde{\sigma}_f,\tilde{\sigma}_{-f}) + \beta \int V_f(I'_f|\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) pr(I'_f|I_f,\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) \tag{15}$$

Then, we can define our equilibrium concept:

Definition 1. ***Equilibrium***

The equilibrium consists of

1. *Price and participation policies* $(\tilde{\sigma}^{*p},\tilde{\sigma}^{*\phi}) : \mathscr{I} \to R^F \times [0,1]^F$
2. *Expected discounted value of current and future net cash flow conditional on own strategies* $\tilde{\sigma}'$*, rivals' strategies* $\tilde{\sigma}$ *at any information set* I_f*:* $\{\tilde{V}_f(I_f|\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) for f \in \{1,...,F\}\}$

such that

1. *Strategies* $\tilde{\sigma}^*_f$ *are optimal when rivals behave according to* $\tilde{\sigma}^*_{-f}$ *at every information set* I_f *for all* f
2. *Firms' beliefs are consistent with equilibrium play in the sense of Equation 14 and Equation 15.*

2.2.1 Discussion

Our approach differs from Ifrach and Weintraub [2017]' moment-based Markov Equilibrium (MME) in computing static profits and transitions from firms' information sets. The main deviation from the MME canonical model is that in dynamic oligopoly games under consumer inertia, as our model, firms' dynamic controls (prices and products) influence both their own and rivals' states, i.e., it is not a capital accumulation game. This implies that firms' strategies affect the aggregate market moments' transition, even if their own states are negligible. Therefore, computing Ifrach and Weintraub [2017]'s approximated transition kernel forward simulating the distribution of payoff-relevant states (and possibly actions and profits) for a *fixed* guess of the price and participation strategies would limit firms strategic behavior. Our approach allows firms to internalize their strategies' impact on the evolution of the aggregate moment.

Even when allowing firms to affect the evolution of the aggregate moments strategically, we could have used Ifrach and Weintraub [2017]'s forward-simulation approach to computing beliefs about rivals states conditional on firms' own information set. Although this approach would better reflect firms' equilibrium play, it would still require parametric approximations to compute firms' beliefs in states outside the recurrent class. This is due to the continuous nature of our state space –customer bases, in particular. In our case, we want to repeatedly iterate over chosen nodes of the customer base, which may or might not be in the recurrent class. Therefore, firms' beliefs at any given visited node are always an *approximation* of the beliefs that arise from the infinitely repeated play at the recurrent class. This approximation introduces some deviation between the states where we compute the beliefs and those at which they are used. Hence, we opt for an approach that constructs only approximately consistent beliefs but is computationally fast. Pareschi [2023] discusses alternative parametric approximation methods to compute beliefs in our setting and compares the equilibrium outcomes that result to the underlying MPE.

More fundamentally, our equilibrium does not address the well-known issues that arise from persistent asymmetric information. In this regard, our choice of the variables that compose firms' information sets is somewhat arbitrary. While Fershtman and Pakes [2012] offers an alternative solution, we are also interested in computing equilibrium policies outside the recurrent class. As highlighted by Aguirregabiria et al. [2021], machine learning and artificial intelligence are promising avenues to tackle this issue.

2.2.2 Implementation

The algorithm for computing the equilibrium is standard and based on approximated value function iteration using parametric interpolation methods (Chebyshev polynomials). We initialize the algorithm using the value function's value at the steady state of the game without entry and exit at every possible choice set. The computation of this steady state is simple since we can circumvent the curse of dimensionality by imposing equilibrium restrictions at a steady state (see Appendix C.2). At each iteration step, firms observe their information sets and choose optimal policies by evaluating payoff-relevant states according to their beliefs. We update firms' values using the new policies and iterate until convergence. Appendix C describes the algorithm in detail.

2.3 Existence & Multiplicity

In Section D, we use simulations to show that an equilibrium exists for a wide range of parameters. However, we do not have a proof of existence. In particular, we cannot use the available results in the literature [Doraszelski and Satterthwaite, 2010, Escobar, 2013] to prove it. Nevertheless, the lack of proof of existence does not arise due to the game's dynamic nature or firms' participation decisions. Consumer inertia introduces heterogeneity into the demand, making it a special case of the mixed logit distribution with discrete types. Thus, we cannot ensure that the optimal price correspondence is convex-valued conditional on rivals' strategies and taking continuation values fixed. This is a well-known problem in the literature, which has prevented the development of general existence results for games of imperfect competition with mixed logit demand, even in static settings.[14]

Furthermore, there is no guarantee that the equilibrium, if it exists, is unique. The sources of multiplicity are hard to isolate as well. On the one hand, dynamic games of price competition with consumer inertia, network externalities, or learning-by-doing are likely to present multiple equilibria [Besanko et al., 2010, Reguant and Pareschi, 2021]. On the other hand, participation costs also introduce multiplicity, even in static games [Pesendorfer and Schmidt-Dengler, 2008].

3 Industry Background

Next, we describe the Uruguayan tobacco market. We observe that consumer choices are persistent. Furthermore, we highlight that the Uruguayan experience provides enough variation in the data to identify the

[14] As noted by Caplin and Nalebuff [1991]: "*Without any restrictions on market demand, it may be that two extreme strategies, either charging a high price to a select group of customers (for whom the product is well positioned) or charging a low price to a mass market, both dominate the strategy setting an intermediate price. This issue has been a major stumbling block in the study of existence*". See Aksoy-Pierson et al. [2013] for a notable exception.

primary sources of inertia: addiction and loyalty. Moreover, we argue that firm behavior is consistent with our model of competition, a point we revisit in Section 4.3.

3.1 Data

We use two main data sources. First, we use store scanner data, which provides information on the quantity and price paid for cigarettes sold between 2006 and 2019. The final sample includes around 100 stores scattered across 40 regions. Aggregate sales in our sample closely track the aggregate national sales according to the Uruguayan tax reports –see Figure B.1.

The market structure is relatively simple. Three players participate in the Uruguayan tobacco market. Monte Paz, a national firm, holds around 75 % of the market, while the two multinationals, Philip Morris and British American Tobacco (BAT), account for 20% and 5%, respectively. There are between 20 and 30 products in the market. However, many of these products share prices, observable characteristics, and are introduced and retired simultaneously. In most of the analysis, we bundle similar products together and refer to them as products or segments. We distinguish between each firm flagship products, other regular products, the light category (low in tar), and other products with special characteristics (slim, longer, etc.). In total, we work with nine product segments. Appendix B.2 presents the details of the product aggregation.

We also leverage an individual panel built by the International Tobacco Control Policy Evaluation Project (ITC). The ITC contacted and interviewed individuals every other year from 2006 to 2014.[15] Originally, the panel included only smokers, but if they decided to quit between interviews, they stayed in the sample. This panel includes information on individuals' smoking status in each wave, quantity smoked, brand, the price paid, age of initiation, time smoking the current brand, demographics, etc. The final sample includes around 1,300 individuals and almost 3,000 choice events. Table B.1 summarizes this information. Additionally, we use other relevant information, such as the population survey (Encuesta Continua de Hogares), to obtain demographics and smoking prevalence at the regional level.

Finally, note that our sample period coincides with the rise of e-cigarette sales in the US [Tuchman, 2019]. However, the commercialization of e-cigarettes is forbidden in Uruguay. Although individuals can buy them abroad and bring them as personal objects, according to tobacco use surveys, less than 10% of individuals have ever used them between 2006 and 2012. Hence, we do not expect e-cigarettes to impact our results significantly.

3.2 Identifying Addiction and Brand Loyalty

3.2.1 Persistent Choices

Table 1 shows the proportion of consumers who repeat choices across waves of the individual panel.[16] First, our sample's overall quitting rate is between 15% and 25%, and the smoking rate for people not smoking in the previous wave is around 21 %. Second, on average, 70 % of smokers repeat their product choice in the next wave.

[15] In demand estimation, we restrict the product-level data to this same sample period.
[16] This should be considered the probability of repeating a choice every two years.

Table 1: Switching matrix for smokers and non-smokers

Smoker Status	Year	Repeat Choice	Smoke
Non Smoker	2010		0.180
	2012		0.226
	2014		0.244
Smoker	2008	0.676	0.823
	2010	0.592	0.773
	2012	0.679	0.807
	2014	0.760	0.867

These figures show that consumer choices are highly persistent. However, we do not know, *a priori*, whether it is due to persistent consumer preferences or structural state dependence [Heckman, 1981]. Indeed, this is the crucial identification challenge in our analysis. Next, we present the sources of variation in our data that help us separately identify the different sources of consumer inertia.

3.2.2 Tax swings

In 2004, Uruguay ratified the Framework Convention on Tobacco Control of the WHO, implementing a wide array of tax and non-price policies to regulate the tobacco industry. These policies included prohibiting all advertising of tobacco products, smoking in enclosed public places, and imposing sizeable pictorial health warnings on tobacco products' packaging.

However, political swings have made the tax policy inconsistent over the years. Taxes increased during 2005-2010, when they reached their highest values, decreased during 2010-2015, and rose again in 2015-2020 when they came close to the 2010 level (as shown in Figure 2) coinciding with the Uruguayan electoral process.

Figure 2: Real Taxes.

These oscillations are a primary source of price variation in our data and a helpful tool to identify smokers' addiction. The ideal experiment to identify addiction is to observe identical individuals facing the same market conditions (prices, choice sets, etc), choosing with and without dependence on cigarettes. We argue tax swings provide variation that resembles this ideal experiment. For instance, initial tax increases (as observed in 2010) make smokers more likely to quit smoking (note the spike in quitting rates in Table 1). Then, the posterior return of taxes to a low level allows us to compare the choices of those who switched out in a similar context as before they quit. To sum up, we can identify the addiction parameter by tracking people over the years and comparing the asymmetry of switching behavior between high and low tax periods. Then, we exploit substantial variation in the product portfolio and relative prices to identify product loyalty.

3.2.3 Portfolio shocks

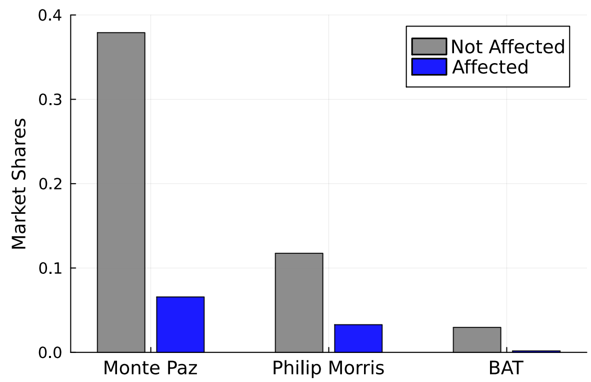
In 2009, the government passed the "one-presentation-per-brand" regulation, which required producers to use a different brand name for each product.[17] Before 2009, all firms structured their product portfolios similarly. They sold several brands. Each brand had a "main" product (the bestseller) and, sometimes, secondary products, usually in the light segment or presenting special characteristics. Thus, all firms had to retire between 20 % and 50 % of their product portfolio from the market, mainly affecting the light product segment. Figure 3 illustrates the relevance of the affected segment within each firm's portfolio. For instance, Philip Morris had to discontinue sub-varieties of the Marlboro brand, which accounted for more than 25 % of total sales.[18] Consequently, consumers had to make new active choices, which aids in identifying state dependence, as in Handel [2013].[19] Formally, it provides an additional moment for identifying brand loyalty: the choice probabilities of an individual who faces addiction yet is not locked into any product.

[17] DeAtley et al. [2018] studied the compliance of the single presentation requirement in Uruguay and found that most firms complied with the norm, although not all respected the spirit of the measure. See Figure B.7 for a representation of how it affected Philip Morris' portfolio.

[18] Philip Morris International and its Uruguayan subsidiary, Abal Hermanos, sued the Uruguayan government because of this policy. They considered it violated international property rights agreements. Philip Morris claimed that the sudden prohibition to commercialize several trademark products under the Marlboro brand caused sizable pecuniary damage. They also alleged that health warnings limited the efficient use of their logos and brand distinctions. Overall, Philip Morris claimed such policies violated property rights agreements and asked for 25 million dollars in compensation. Uruguay finally won the case, and both norms are still in place.

[19] This is not precisely the setting in Handel [2013] since individuals are forced to choose without changing the choice set. However, we can think of his setting as products going out of the market and being introduced anew.

Figure 3: Shares by Firms' Portfolio



Note: The figure shows each firm's average shares by product one year after the one-presentation-per-brand is passed.

3.2.4 Large Change in Relative Prices

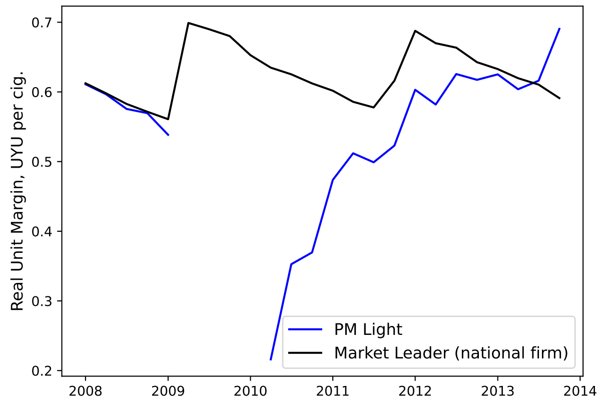
Although the complete elimination of products is an ideal source of variation to identify product loyalty, less drastic changes in static valuation also aid identification. In particular, relative price shocks provide information to determine product loyalty. The intuition is analogous to the tax variation we used to identify addiction. Ideally, we would like to observe the same individuals making choices under the same prices (and market conditions in general) when patronizing different products. In that sense, large and transitory relative price shocks are valuable for identifying loyalty because they shift consumers' loyalties and revert to the same market conditions. Indeed, this is the type of variation previously utilized to identify brand loyalty by Dubé et al. [2010] and switching costs by Pakes et al. [2021].

Our data also contains large relative price swings as well. Philip Morris suffered the largest impact from the policy because a larger share of its products shared brand names, and it could not replace products immediately.[20] Despite Philip Morris' flagship brands retaining a fraction of the consumers whose products disappeared, its market share decreased in the months following the policy. Hence, one year after the policy began, the company reintroduced products in the light segment, setting strikingly low prices–with respect to the market average and Philip Morris' prices before the policy was passed. Figure 4 shows per-cigarette unit margins relative to taxes. While unit margins were around 0.5-0.7 before the policy, they dropped to about 0.10-0.25 between January and March 2010. They returned to the original level around 2014.[21]

[20]Informal talks with industry agents suggest that international property rights agreements delayed the introduction of new brands to the country.

[21]25 % of the drop was due to nominal price drops, while the other 75 % was due to tax increases not passed to prices.

Figure 4: Philip Morris' real unit margin.



Note: The unit margin is computed against the taxes. It does not include any other marginal costs the firm might have while producing cigarettes.

The policy-induced price changes interact with the product offerings in the market, providing insight into consumer loyalty since it allows us to see "active" consumers' choices across different price scenarios. Our setting offers such variation. For instance, when the policy forced several products out of the market, relative prices between the firms were quite similar. However, following Philip Morris's substantial price drops to reintroduce its products, BAT withdrew its offerings. At this point, the relative prices swung to about 45 % lower for Philip Morris than the national firm. Comparing consumer substitution between Philip Morris and BAT during these events helps gauge their price sensitivity independently of any loyalty factor. Appendix B.4 evaluates this variation in more detail through an event study following products' discontinuation from stores. See also Figure B.4 for a summary of product entry and exit frequency and timeline.

3.3 Firm behavior is consistent with competition under inertia

Finally, we stress that the policy provides ideal variation to validate the conduct assumptions in our model. If consumers' choices are entirely due to persistent preferences, then firms have no incentives to invest or harvest consumers, and the model reverts to a static competition model. For instance, we would require artificial, often implausible, cost changes to justify the aggressive introduction of new products, as in Figure 4. However, if consumers are state-dependent, firms can affect future demand by changing prices today, which appears consistent with firms' aggressive penetration pricing strategies.

Additionally, in markets where consumers are presumed to have inertia, the joint estimation of demand and supply can substantially improve our ability to infer the elusive nature of persistent choices. However, the computational burden of solving dynamic games still makes this approach infeasible for most applications. In this paper, we take an intermediate step in this direction. In Section 4.3, we leverage these insights to evaluate further whether firms' behavior is compatible with our estimated levels of inertia. Nonetheless, we believe that making progress in computing dynamic games to identify consumer inertia from demand and supply information jointly is a promising avenue for future research.

In summary, significant regulatory changes make the Uruguayan experience ideal for identifying consumer addiction and loyalty. Variation in price and product assortment enables the identification of persistent preferences from state dependence. Moreover, significant firm responses to regulation allow us to validate our estimates of consumer inertia.

4 Estimation

There are three sets of primitives to recover from data: consumer preferences, marginal costs, and participation costs. We first describe demand estimation and then move to the supply side.

4.1 Demand

We combine individual-level data with aggregate market shares to estimate demand. We maximize the likelihood of observing individual i choosing product j at market m at time t, restricting product mean values to be consistent with the observed shares across markets. Then, we regress mean utilities on product characteristics and prices to recover the remaining structural parameters.

Consumption Probabilities Let $\bar{u}_{ijtm}(z;\mu^D) = \delta_{jtm} + \sum_r \sum_k (D_i^r X_j^k)\gamma^{kr} + \eta_0 1\{z \neq 0\} + \eta_1\{z = j\}$, and assume ε_{ijtm} has the type-I extreme value distribution i.i.d. across individuals, products, markets, and time. Then the probability of consuming product j, conditional on being affiliated to the product z last period is,

$$s_{ijtm}(z;\mu^D) = \frac{exp(\bar{u}_{ijtm}(z,\mu^D))}{1+\sum_k exp(\bar{u}_{iktm}(z,\mu^D))} \tag{16}$$

where $\mu^D = \{\delta, \gamma, \eta\}$

Market Level Shares Then, market-level shares depend on state and demographic-specific choice probabilities $\{s_{ijtm}(z,\mu^D)\}$, and the joint distribution of demographics and affiliations at market m at period t. We express them as

$$S_{jtm}(\mu^D) = \int s_{ijtm}(z;\mu^D)dF_{tm}(D_i,z)$$

Although we observe the marginal distribution of states $dF_{tm}(z)$–determined by past market shares–and the marginal distribution of demographics $dF_{tm}(D_i)$ from population surveys, we do not know the joint distribution of demographics and affiliations at the market level. To construct it, we leverage the individual level data and assume that the distribution of demographics conditional on previously patronized products is not store specific, i.e., $dF(D_i|z)$. Nevertheless, we let the demographics conditional on not smoking vary across stores. Then, we can express the joint distribution of demographics and affiliations using the market-specific distribution of states and the average distribution of demographics conditional on states.[22]

[22] We perform a sensitivity analysis to this assumption, where the individual-level data is informative about $dF(z_j|D)$ and obtain $dF_{tm}(D_i|z)$ by Bayes rule updating the prior over demographics at each store. See Appendix E.

If aggregate market share under affiliation z is $S_{jtm}(z,\mu^D) = \int s_{ijtm}(z;\mu^D)dF(D_i|z)$, then, taking into consideration that affiliation is a discrete random variable, aggregate market shares can be expressed as

$$S_{jtm}(w;\mu^D) = \sum_{z\in\{1,\dots,J\}} w_{tm}(z)S_{jtm}(z;\mu^D) + w_{tm}(0)S_{jtm}(0;\mu^D)$$

where $w_{tm}(z) = S_{z,t-1,m}$

In the first stage, we solve the following problem:

$$\begin{aligned} &\min_{\theta} \frac{1}{N}\sum_{i}\sum_{\mathbb{J}_i} 1\{\daleth_i = j\} \times log(s_{ijtm}(\daleth_{i,t-1};\delta,\theta)) \\ &s.t \quad S_{jtm}(S_{j,t-1,m},\delta,\eta,\lambda,\gamma) = \hat{S}_{jtm} \end{aligned} \tag{17}$$

This approach resembles Goolsbee and Petrin [2004]'s method. However, it requires adapting a few case-specific implementation details. Although consumers report choices over eight quarters, we assume the relevant time horizon for firms is one year. Hence, we simulate an intermediate choice for which we have no information, which mimics consumers' yearly choices and allows us to estimate dynamic preferences at the annual level. Second, we do not observe the stores where consumers shop. Thus, we assign them to markets probabilistically. These probabilities depend on the chosen products over the periods, consumer and market demographics, and the size of stores.

Finally, to construct the outside option, we assume every store could sell cigarettes to 35% of the store's customers, which was the national smoking rate in 2001. To determine the number of store customers, we assume they are currently selling cigarettes to a proportion of customers that coincides with the current smoking prevalence within the market in which stores operate. At the aggregate level, this implies that the outside option oscillates between 30% and 45% over our sample period. Estimates are not particularly sensitive to the baseline market size definition.

In the second stage, we decompose mean utility through linear regression,

$$\delta_{jtm} = \delta_{tm} + \delta_j - \alpha p_{jt} + \Delta\delta_{jtm} \tag{18}$$

At this stage, we face the usual endogeneity problem between prices and unobserved utility $\Delta\delta_{jtm}$. However, our institutional setting and the available data make this issue less relevant. First, prices are set nationally, and almost all stores abide by suggested prices. Thus, p_{jt} is unlikely to be correlated with time-product-market and product-market unobserved shocks. Second, we can control for time-market and product fixed effects. Finally, we instrument for product-time unobserved shocks using taxes. During our sample period, there were changes in excise and value-added taxes, which created variation at the time-product level.

4.1.1 Results

Inertia Inertia is high. Indeed, smokers are willing to pay almost two times the average price for any cigarette. Moreover, they are willing to pay around three times the average cigarette price to repeat their product choice. Naturally, firms do not only target repeated customers, which allows these consumers to pay lower prices than their willingness to pay. There is also a modest amount of consumer heterogeneity. In particular, educated and young customers are less price-sensitive and value light products more. Table 2 presents a summary of consumer preference estimates. Overall, the demand model accurately captures switching patterns between products and in and out of smoking –see Table E.1.

Table 2: Demand Estimates

		Complete Secondary	Working Age
Real Price Per Cig	-0.931	0.046	0.421
s.e	(0.033)	(0.032)	(0.029)
Light		0.080	0.100
s.e		(0.147)	(0.154)
Premium		-0.194	0.259
s.e		(0.136)	(0.124)
Addiction	2.007		
s.e	(0.055)		
Brand Loyalty	3.437		
s.e	(0.045)		
N Individuals Observations	2850		
N Markets	12422		

Elasticity These estimates imply that the mean own-price elasticity in the market is around -0.9. Although it is low compared to other industries, it is consistent with the scarce literature treating cigarettes as a differentiated product [Ciliberto and Kuminoff, 2010, Liu et al., 2015]. Indeed, the fact that firms price many products in the inelastic portion of the demand curve is additional evidence that dynamics play an essential part. Additionally, the implied aggregate market elasticity is slightly below 0.4, in line with a large body of work computing smoking elasticities.

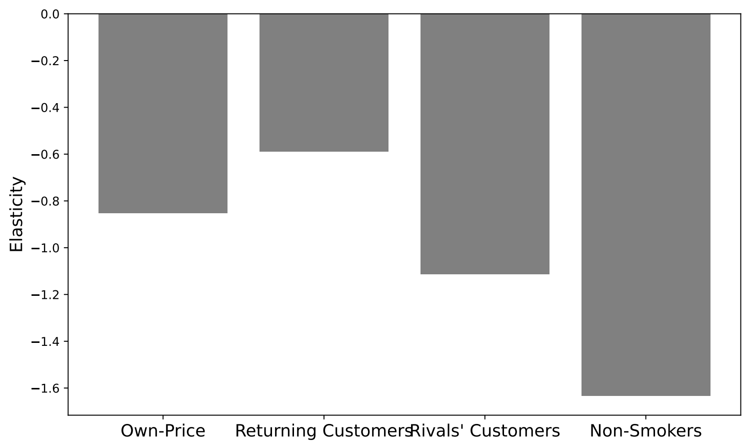
Table 3: Demand Elasticity

	Own-Price	Agg. Market
Baseline Estimates	-0.853	-0.346
Prev. Literature	[-1.35, -0.77]	[-0.5, -0.15]

Note: Median elasticity in previous literature refers to Ciliberto and Kuminoff (2010) and Liu et al. (2015), the only references that treat cigarettes as differentiated products. Market reports range from Evans and Farrely (1998).

Finally, we underscore that the elasticity is a weighted average of group-specific elasticities. In particular, it is an average of the sensitivity of returning and new customers and non-smokers. Figure 5 illustrates that rivals' consumers and non-smokers respond proportionally more to prices than their own customer base. Hence, as the participation of locked-in customers in total purchases increases, the demand becomes increasingly more inelastic.

Figure 5: Elasticity decomposition



Note: Within consumer-group elasticities are calculated as: $\frac{\partial s_j(k)}{\partial p_j} \frac{p_j}{s_j(k)}$. The aggregate elasticity is a weighted average of the within consumer-group elasticities, where the weights are the share of each consumer group on total purchases: $\frac{\partial s_j}{\partial p_j} \frac{p_j}{s_j} = \sum_k \left(\frac{w(k) s_j(k)}{s_j} \right) \left\{ \frac{\partial s_j(k)}{\partial p_j} \frac{p_j}{s_j(k)} \right\}$. See Appendix A.5

4.2 Supply

The remaining unknown primitives of the model are marginal costs and the distribution of participation costs. We face a few challenges in estimating these primitives. Firms make pricing decisions at the national level, meaning that we observe a single market. Hence, despite substantial variation in observed states, we cannot apply solution-free estimation methods, as in Bajari et al. [2007].[23] Instead, we must rely on a "full-solution" approach.

Although a full-solution approach is computationally feasible due to our equilibrium notion, it still requires overcoming a few hurdles. First, we cannot break up the problem between static and dynamic controls since entry/exit probabilities affect expected continuation payoffs and, to that extent, prices. Thus, we cannot follow most of the recent dynamic estimation literature that recovers marginal costs from static pricing conditions and then construct a maximum likelihood estimator solving the dynamic entry game, for instance, Igami [2017], Igami and Uetake [2020], Rysman et al. [2021], Elliott [2022]. In addition, there are no guarantees that the game's equilibrium is unique, which challenges identification.

In this section, we describe the estimation approach in detail, highlighting how we overcome each one of these challenges. First, we present the econometric model. Then, we show how to derive moment conditions and discuss identification. Finally, we discuss how to address potential multiplicity. Appendix C and Appendix F discuss computational and estimation details, respectively.

[23]See Fleitas [2017] for an application of two-step methods in the context of consumer inertia.

4.2.1 Econometric Model

Our model has two sources of statistical noise: a common knowledge shock to the time-varying marginal costs and an unobserved, private information shock to fixed costs. The introduction of these shocks does not increase the dimensionality of the problem at all. We solve the game's equilibrium at different cost nodes and integrate the policies over the unobserved shocks during the moment construction. Moreover, we impose parametric assumptions, allowing us to integrate out these shocks within the dynamic game.

We assume the common marginal costs are taxes plus an unobservable part.

$$c_{kt} = \theta_k^{vc} + tax_t + \sigma_{\varepsilon^c}\varepsilon_t^c$$

where $\{\theta_k^{vc}\}$ are parameters to recover from data, tax_t is observable, and ε_t is an unobserved marginal cost shock common to all products. It is distributed $N(0,1)$ and σ_ε is a parameter we wish to estimate.

The second source of statistical noise comes from random fixed costs. We wish to identify and estimate the mean of their distribution. We assume all firms face the same fixed-cost distribution, whose average value decreases with the number of products they sell.

$$\mu^{FC}(N) = \theta_S e^{-\theta_R(N-1)}$$

θ_S regulates the scale of the mean value of the fixed cost distribution, while θ_R regulates the rate at which they decrease with the number of products. In particular, we can interpret θ_S as the costs of distributing a single product. (θ_S, θ_R) are parameters to recover from data. Finally, we assume the distribution of participation costs is distributed exponentially.[24] Using this assumption, we can express expected fixed costs conditional on offering the product as,

$$E\left[\Theta_k \times 1\{\Theta_k \leq \bar{\Theta}(\mathbb{X}', \sigma_{-k}^{\phi})\}\right] = \sigma_k^{\phi} \times \mu_k^{FC} - (1-\sigma_k^{\phi}) \times \bar{\Theta}(\mathbb{X}', \sigma_{-k}^{\phi})$$

which simplifies the computation of continuation values and their derivatives.

4.2.2 Estimation Method

Exogenous states' transitions. Our model has two exogenous transitions: the common component of marginal costs and the mean valuation of inside products. We assume they follow independent AR(1) processes. Then, we recover the parameters of the tax process by fitting an AR(1) process to the data.

[24]Exponential distributions of fixed costs are prevalent in the dynamic entry/exit literature (see Pakes et al. [2007]) because of its memoryless property: expectations, conditional on participation, can be expressed in closed form, getting rid of complicated integrals.

$$tax_t = \mu^{tax} + \rho^{tax} tax_{t-1} + \sigma_{\varepsilon^{tax}} \varepsilon_t^{tax}$$
$$\hat{\delta}_t = \mu^{\hat{\delta}} + \rho^{\hat{\delta}} \hat{\delta}_{t-1} + \sigma_{\varepsilon^{\hat{\delta}}} \varepsilon_t^{\delta}$$

Simulated Method of Moments After estimating demand primitives and exogenous state transitions, there are $J+3$ remaining parameters: $\theta = \{\theta_k^{vc}, \sigma_{\varepsilon^c}, \theta_S, \theta_N\}$. We estimate them using the simulated method of moments (MSM). According to our model, discrete participation decisions are described by the policy $\tilde{\sigma}^{\chi}(z_t^f, \xi_t; \varepsilon_t^c, \Theta_{kt}; \theta)$ (recall that $z_t = (S_{t-1}^f, \bar{S}_{t-1}^f)$, and $\xi_t = (\mathbb{J}_t, c_t, \delta_t)$). Thus, at the true parameters θ_0,

$$\chi_{kt} = \sigma_k^{\chi}(z_t^f, \xi_t; \varepsilon_t^c, \Theta_{kt}; \theta_0)$$

Equivalently, prices are determined by the optimal policies and marginal cost shocks (they do not depend on the fixed cost's realization of the private shocks):

$$p_{kt} = \sigma_k^p(z_t^f, \xi_t; \varepsilon_t^c; \theta_0)$$

Thus, given the observed data $\{\chi_{kt}, p_{kt}, \{z_t^f\}_f, \xi_t\}_{i=1}^{J\times T}$[25], an MSM estimator of θ_0 can be generated from the conditional expectations:

$$E[\chi_{kt} - E[\sigma_k^{\chi}(z_t^f, \xi_t; \varepsilon_t^c, \Theta_{kt}; \theta_0)|z_t, \xi_t]|z_t, \xi_t] = 0$$
$$E[p_{kt} - E[\sigma_k^p(z_t^f, \xi_t; \varepsilon_t^c; \theta_0)|z_t, \xi_t]|z_t, \xi_t] = 0$$

Appendix F.2 shows how to use importance sampling to reduce the computational burden of the estimation procedure. Standard errors are computed using the usual method of moments formula.

4.2.3 Identification

Next, we describe how we identify firms' marginal and fixed costs. We first describe how conduct jointly informs us about marginal costs and next-period portfolio probabilities. Then, we explain what variation in the data helps us recover the marginal cost function and fixed costs.

Conduct To evaluate how conduct (in our case, dynamic competition under consumer inertia with entry/exit) informs the problem, we compare it to the usual static FOC inversion to recover marginal costs when static Nash-Bertrand competition with differentiated products is assumed. In our setting, the central challenge is that fixed costs influence firms' prices through the choice set probabilities. For instance, a firm

[25] The number of observations is not precisely $J \times T$ since prices are only observable if the products are currently in the market. We do not make it explicitly in the notation to avoid overloading it.

that knows a product will likely exit the market will not invest in building a large customer base and increase prices accordingly. Thus, our conduct assumption does not directly map observed prices to marginal costs. However, we also observe participation decisions. We argue that prices and participation choices provide two distinct sequences of marginal cost and continuation probabilities that rationalize them. In a way, we highlight that prices and participation FOC are not collinear. Hence, the static FOC inversion has an equivalent representation in the dynamic model. Figure F.1 presents a graphical illustration of this argument. There, we show that the sequence of marginal and fixed costs that generate alternative BAT's flagship average prices and participation rates. Then, observed prices and participation select different cuts of the plane.

Variation in the Data We are simply estimating product-specific time-fixed marginal costs. Hence, average prices in the data –given estimated levels of inertia and conduct– are informative about marginal costs. Additionally, we leverage the correlation between participation choices and observed states (tax rates and customer bases throughout time), which is standard in the entry/exit literature. In fact, we are not fully exploiting all the information available in the panel of product assortment choices. We could have used the score of the likelihood of participation decisions as moments in the data, which would resemble the approach taken by Igami [2017], Igami and Uetake [2020], Elliott [2022].

Interestingly, the correlation between prices and the customer base also informs fixed costs. Suppose we observe a large drop in the loyal base without a significant price response. This points out that firms assess the product's probability of leaving the market to be high, which informs fixed costs.[26] Similarly, larger unobserved cost shocks implied lower prices and lower pass-through, while higher marginal costs mean higher prices and lower pass-through. Hence, the level and correlation of prices with taxes help tease apart the product's marginal cost from the common unobserved shock.

4.2.4 Multiplicity

If multiple equilibria are possible, the probabilities of participation–and, to a similar extent, prices– cannot be pinned, and the moments, or likelihood function, would not be well-defined [Tamer, 2003]. We address potential equilibrium multiplicity in two stages. First, we use different methods to argue that the dynamic pricing game without entry and exit has a unique equilibrium for large regions of the parameter space. Then, we use the steady state of this game to provide natural initial values across different parameterizations, which acts as a way of choosing one of the equilibria in the game with entry and exit. We refer the reader to Appendix D for details.

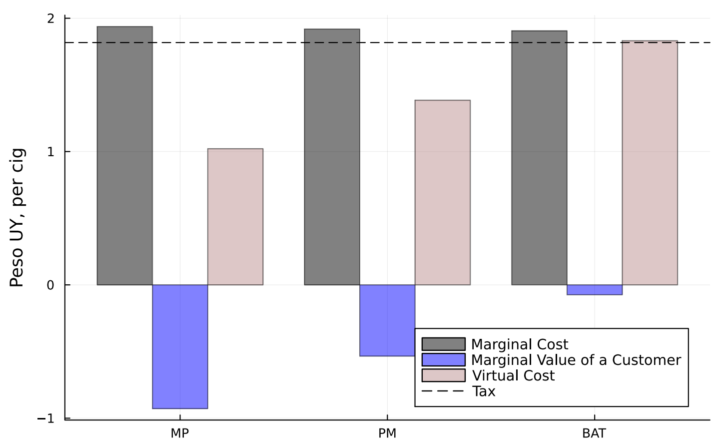
4.2.5 Results

Overall, the estimated marginal costs of production (without considering taxes) are small and homogeneous, in line with accounting estimates. For all firms, taxes represent more than 90% of marginal costs. Figure 6 shows the average marginal costs —taxes included. On the other hand, virtual costs are heterogeneous across

[26] We are unaware of previous work that exploits firms' prices to identify fixed costs in dynamic settings. See Berry and Pakes [2000] for early work suggesting a similar approach.

firms and products. Recall that we interpret $\tilde{c}_{kt} = \left(c_k - \frac{\beta}{M}\frac{\partial EV_f}{\partial S_{kt}}\right)$ as the virtual cost of selling a cigarette, and noted that firms markup products with respect to this measure. Thus, Figure 6 compares average after-tax costs with average dynamic incentives concerning products' own share.[27] The national firm's virtual cost of selling cigarettes is half its marginal costs. On the other hand, BAT's virtual costs are not so different from actual marginal costs.

Figure 6: Average Real Costs and Virtual Costs



Note: The figure shows the average marginal costs for each firm. The blue bars show the average real marginal costs, while the orange bars show the average virtual costs. The latter is computed as the average real marginal costs minus the average dynamic incentives.

The mean value of the fixed-cost distribution is low and relatively constant as firms add new products. The expected fixed costs paid represent around 40% of the variable profits the firms make. Figure F.3 presents the fixed cost distribution function, Table F.2 presents the full estimation results. The tax and preferences' process estimates are also shown in Table F.1.

4.3 Model Validation - Firm Behavior under Consumer Inertia

In markets characterized by consumer inertia, firms' strategies provide crucial insights into differentiating inertia from mere persistent preferences. Although we are not using firm behavior to estimate consumer preferences, in this section, we argue that firms' pricing strategies are consistent with the conduct assumption –forward-looking behavior under consumer inertia– under the estimated levels of addiction and brand loyalty.

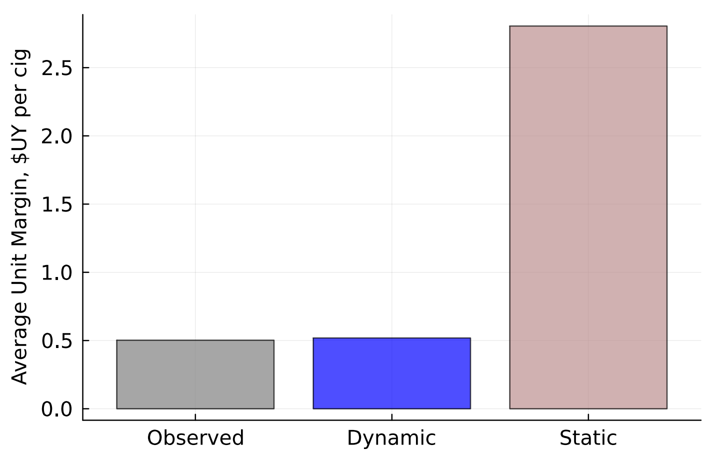
We highlight two features that allow us to validate our assumptions. First, the model can rationalize relatively low unit margins despite exceptionally low elasticities (in this section, we interpret unit margins as the difference between prices and estimated marginal costs, *not* virtual costs). Second, our model accommodates the striking price drops observed in the data and discussed in Section B.

[27] These incentives are computed at the average value of the estimated parameter distributions.

Average Unit Margins: Price insensitive versus Inert Consumers Demand elasticity is determined empirically through the response of demand to prices. However, multiple explanations can determine the observed elasticity. In particular, low elasticity can be explained by either consumers' low disutility from prices or inertia. Distinguishing between the two has crucial implications for firms' optimal markups. If consumers face inertia and firms are forward-looking, low elasticity occurs together with high investing incentives, which decrease virtual costs. Hence, firms' unit margins –the difference between *actual* costs and prices–are not only determined by consumers' response to prices. On the other hand, if consumers do not derive disutility from high prices or companies are myopic, firms are not willing to invest in the customer base. Thus, they set higher markups.

In our first test, we compare the prices that firms would have set if 1) inertia is at our baseline estimates and 2) there is no inertia and the observed demand elasticity is entirely generated from consumers' low disutility from prices–which can also be interpreted as myopia on the firm side.[28] To analyze the latter case, we find the price coefficients and mean utilities in consumer preferences that would generate equivalent market shares and price elasticity at the prices observed in the data. We then solve the equilibrium prices for the case without inertia at the estimated marginal costs.[29] Observe this is a static model whose Nash-Bertrand equilibrium can be solved independently for each choice set. Figure 7 shows the predicted weighted average unit margin in both cases and compares it to the observed ones.

Figure 7: Price Comparison, Static v. Dynamic



Note: The static model is computed by finding the price sensitivity and mean utilities that would generate equivalent market shares and price elasticity at the observed prices. Then, we use these new parameters to solve the static Nash-Bertrand equilibrium of price competition. The dynamic model evaluates the MME's policies in the observed states.

When consumers do not respond to prices due to low disutility, firms' unit margins are significantly higher than observed. In other words, a static model, or equivalently an assumption of firms being myopic, would need big negative costs to accommodate the data. The intuition is simple. Without inertia, consumers do

[28]Low disutility from prices and myopia are not precisely equivalent because, in the latter case, firms would still interpret that changes in the customer base modify the elasticity of demand. However, it is alike for comparing the *average* markups over time, where we aggregate over all possible states.

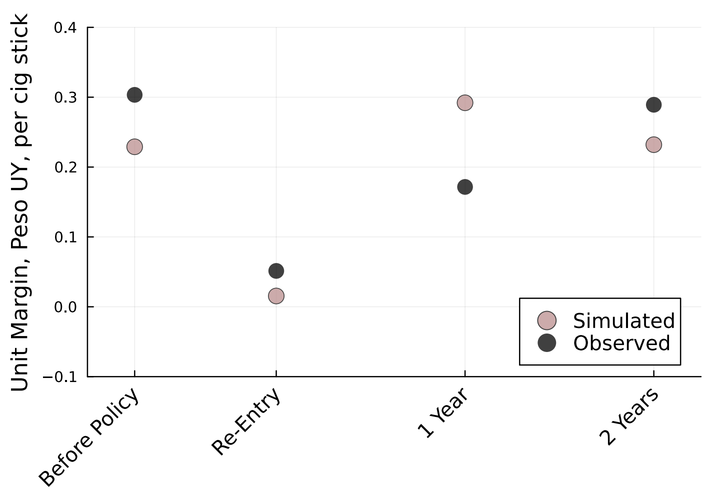
[29]We could do this at the tax level and obtain similar results, recall that estimated marginal costs are close to 0.

not provide any long-term value for the firm. Hence, firms are not constrained to raise markups, and prices are much higher. In the dynamic case, low elasticity is partially explained by consumers' state dependence. In that case, low consumer responsiveness to prices is compensated with lower virtual costs, and prices stay relatively low despite strikingly low elasticity.

Introductory pricing: investing in consumers Our previous analysis suggested that firms are indeed forward-looking, and they lower average prices to account for the long-term value customers bring to companies. Now, we also argue that firms' "harvesting" is consistent with the estimated levels of inertia. That is, we illustrate that the observed firms' price responses to changes in the size of the locked-in customer base are consistent with our model of competition under the estimated consumer preferences. In particular, we evaluate whether our estimated levels of inertia can rationalize the aggressive price discounts offered at the products' introduction without relying on marginal cost changes.

In the second test, we compare Philip Morris's aggressive introductory pricing strategy with the model's prediction. Figure 8 shows observed and predicted unit margins for the Philip Morris light segment at several periods. We see that the model predicts a sharp margin drop. While minimum margins are almost identical, the expected margin drop is slightly lower than observed. We note that Philip Morris's prices at the moment of reintroducing products were around marginal costs. Figure 8 illustrates that pricing at cost when introducing a product can be rationalized by our conduct assumption under the estimated levels of inertia. If persistent choices were entirely due to persistent preferences, firms would not have incentives to modify prices as a response to changes in the customer base, which confirms that firms believe inertia is at levels similar to those we have estimated.

Figure 8: Philip Morris Price Drop



Note: The figure shows the observed and predicted unit margins for the Philip Morris light segment at several periods. At the time of re-entry, we set the Philip Morris light segment's loyal base to 0 and evaluated prices according to the equilibrium policies. We average the observed and simulated values for the first two quarters of 2010 (re-entry), as tax changes make it hard to determine whether the firm was setting prices considering the new tax level. Then, the one, two, three, and four years after evaluating simulated and observed prices in the first quarter of every year.

Pricing at costs warranted Philip Morris a lawsuit from the national firm for predatory pricing.[30] In that instance, prices were proved to be below costs, and the defendant did not argue that price drops were due to cost shocks nor that there was any significant change in the firms' cost structure. Interestingly, our model allows us to decompose firms' prices between "investing" incentives and predatory ones. In this case, pricing patterns are consistent with a story of investing in consumers, but we delay the actual decomposition to Section 5.

Overall, at the estimated levels of inertia, our competition model captures optimal markups and price response to changes in the customer base well. Indeed, we have seen that assuming consumers do not derive disutility from prices, that persistent choices are due to persistent preferences, or that firms are myopic, would have generated less sound patterns. This analysis confirms that our model of competition, embedded with our empirical estimates, is a good approximation of the actual market dynamics. In Appendix F.4, we also show that under the estimated primitives, the long-run steady state of the economy fits shares, prices, concentration ratios, switching patterns, and elasticity very well.

5 Reducing inertia in tobacco markets

In this section, we use our estimates to analyze the effect of reducing consumer inertia on tobacco consumption. We do so in three steps. First, we reduce the degree of brand loyalty, holding addiction fixed. We assume that reducing brand loyalty does not induce more smokers to quit at observed prices, but they are more likely to switch between products. We then evaluate the effect of lowering addiction while fixing brand loyalty. Lastly, we discuss combining inertia-reducing policies with taxation to lower smoking rates.

Our key result is to notice that once we account for firms' dynamic incentives, tobacco companies' response to lower inertia is unlikely to reverse the direct effect on consumers. Declining inertia makes consumers less likely to repeat their choices over time, which reduces the long-term value customers add to the firm. Thus, firms become less willing to price aggressively or offer steep discounts to lock customers into their products. This dynamic incentive mitigates and even reverses the negative consequences of making consumers more price-elastic and facilitating the introduction of new products. We stress that this counterbalancing factor would not be present if we did not consider firms' dynamic incentives, which we have shown are relevant for firm behavior.

First, we analyze the equilibrium effect of reducing brand loyalty. In this case, the policy facilitates switching between products without lowering consumers' cigarette valuation. In this scenario, demand becomes up to three times more elastic, which would induce large price drops if firms were not forward-looking. Moreover, entry becomes easier, and the number of available products increases up to 30% when we completely eliminate brand loyalty. Still, according to our estimates, the decrease in firms' incentives to attract consumers mitigates any potential negative impact of the policy, even under conditions seemingly unfavorable to the policy's success. Indeed, for significant brand loyalty reductions, lowering incentives to entice con-

[30] In the first instance, Philip Morris was found guilty of predatory pricing practices but acquitted in 2018 by a higher court. This lawsuit provides rare insights into Philip Morris' motivation behind its aggressive price strategy. Philip Morris alleged that *"Philip Morris reduced its suggested prices to consumers and dropped wholesale prices" [to] "...revert the dramatic market share lost due to Monte Paz response with respect to OPPB..."*. Authors translation from Spanish version.

sumers decreases aggregate consumption despite the substantial increase in demand elasticity and product variety. Similarly, reducing addiction becomes more effective at lowering smoking rates once we account for firms' responses. Because firms internalize that consumers are more likely to quit (switch to the outside option), they stop trying to capture them as aggressively as before implementing the policy. This new optimal strategy constrains the expansion of smokers more than if firms continued to play their previous strategies.

Next, we explore these results and their mechanisms in detail. For each counterfactual level of inertia, we solve equilibrium policies (prices and participation) and simulate the industry for 50 periods 2,500 times. All the results we present in this section are the average across time and simulations. In Appendix G, we show the long-run distribution of states. We keep estimated firms primitives fixed.[31]

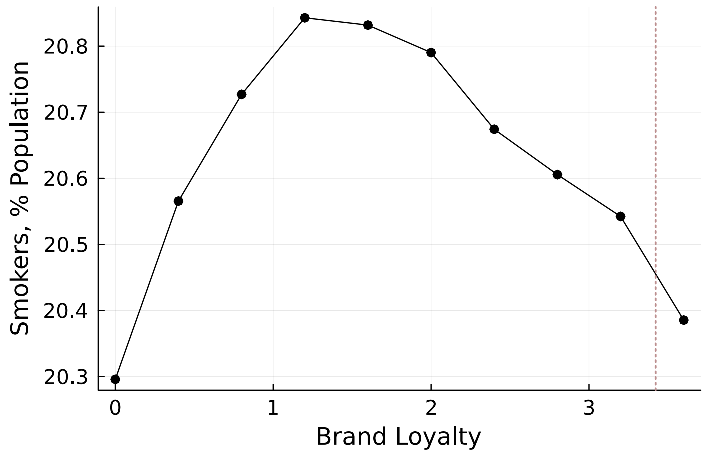
5.1 Brand Loyalty

The direct effect of reducing brand loyalty makes consumers more likely to switch products. This implies that the probability of repeating product choices over time decreases, customers become more price elastic, and their cigarette valuation remains unchanged. Note this analysis constitutes a worst-case scenario from a policy point of view. We are stacking the deck against policies that reduce brand loyalty, such as uniform packaging, since they could also make cigarettes less appealing for both current smokers and non-smokers. Our analysis, however, allows us to isolate firm responses from changes in the mean valuation of cigarettes.

Aggregate Consumption Even in this unfavorable case for the policy, firms' responses are unlikely to increase consumption meaningfully. Figure 9 shows that reducing brand loyalty has minor and non-monotonic effects on tobacco consumption. If policies cut consumers' loyalty in half, the average smoking rate in the country could increase up to 0.4 p.p (1.9%) from our baseline. Moreover, if the policies cut brand loyalty substantially, smoking rates decline by 0.2 p.p. (0.9%)

[31]The only difference with the estimated model is that firms assume the tax level and mean utility process are fixed at the mean value instead of allowing for the fully flexible Markov process.

Figure 9: National smoking rate under counterfactual brand loyalty.

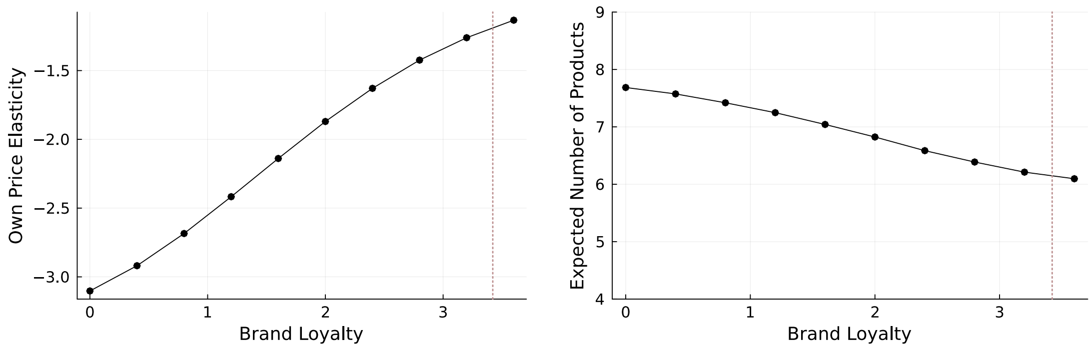


Note: For each level of inertia, we solve for equilibrium policies for prices and market participation. Then, we simulate the industry evolution over 50 periods, replicated 2,500 times from a null industry scenario. The depicted results are the averages across time and simulations. The distribution of visited states is presented in Appendix G. The average smoking rates are computed assuming that the available market size represents 35.6 % of the population, which was the average smoking rate in Uruguay in 2000. The vertical dotted brown line references estimated levels of inertia.

Demand Elasticity & Product Availability The policy does not backfire even though own-price elasticity increases up to three times and product availability grows substantially. Recall that the change in customers' price sensitivity was at the heart of tobacco companies' arguments against uniform packaging.[32] Our estimates confirm this idea. In Figure 10a, we show that average own-price elasticity (at the steady state distribution) increases sharply as we reduce brand loyalty. When we eliminate it entirely, demand elasticity is three times higher than our baseline estimates. If firms were myopic, this would have led to a substantial price decrease and a rise in consumption.

[32] As a reminder, the tobacco companies claimed: uniform packaging was going to *"reduce brand loyalty, causing smokers to switch to cheaper brands and encouraging price competition between manufacturers"* [Chantler, 2014, pp. 5].

Figure 10: Long Run Industry Outcomes - Elasticity and Number of Products



(a) Own-price elasticity

(b) Product availability

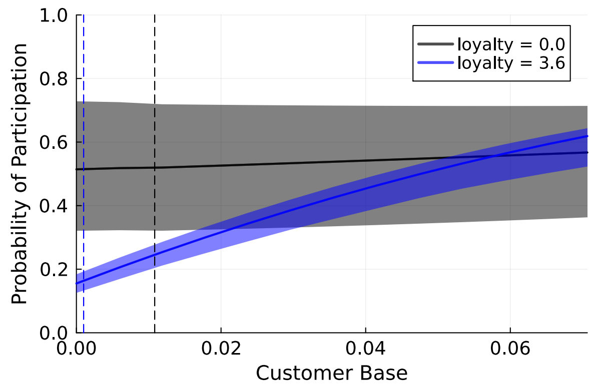
Note: For each level of inertia, we solve for equilibrium policies for prices and market participation. Then, we simulate the industry evolution over 50 periods, replicated 2,500 times from a null industry scenario. The depicted results are the averages across time and simulations. The distribution of visited states is presented in Appendix G. The average smoking rates are computed assuming that the available market size represents 35.6 % of the population, which was the average smoking rate in Uruguay in 2000. Long-run average market shares are used as weights for price statistics. The vertical dotted brown line references estimated levels of inertia.

In addition, reducing brand loyalty increases the equilibrium number of products being offered –see Figure 10b. To understand this result, observe that by reducing brand loyalty, the gains from making an individual addict are shared across all firms in the market. In principle, this facilitates the entry of small products since firms can free-ride on the efforts of their rivals. However, the final effect on the equilibrium number of products is not as straightforward. The increase in price competition induced by lower inertia could also potentially make it less profitable to enter the market. Moreover, higher brand loyalty might make it less likely to discontinue a product once it has reached a significant locked-in customer base.[33] Under our estimates, the first effect dominates. As a result, lower inertia leads to more available products.

We provide some intuition for this result by showcasing BAT Premium's optimal participation rates for varying loyalty levels in Figure 11. Solid lines represent the average likelihood of offering a product, while the ribbon around the lines indicates the range of possible participation rates depending on rivals' positions.

[33]In these counterfactuals, we limit the extent to which the discontinuation effect might operate because we are not allowing the flagship products of the leading firms (Monte Paz and Philip Morris) to be discontinued. We assume this since we do not observe such events in the data. Hence, it is hard to account for the underlying fixed costs of these products.

Figure 11: Participation Policy - BAT, Premium.



Note: This figure represents the policies when marginal costs equal 1.8 U$. The shaded region indicates all the possible values the policy might take for a given size of the product's customer base. The policies are constructed by solving the model at the average parameters of the importance sampling distribution under the indicated levels of inertia.

At our baseline levels of brand loyalty, a rising locked-in customer base causes participation rates to increase, reducing the chances of product discontinuation. However, the entry probability is low (the participation rate at the origin), signaling that stealing consumers from rivals is costly. Because this product has a relatively low baseline probability of participation, it never reaches a sustainable customer base. Hence, even if it enters the market, the product is discontinued shortly after. Moreover, at our baseline estimates of brand loyalty, equilibrium participation rates depend almost exclusively on the size of the products' own locked-in customer base (the blue ribbon is very narrow).

On the other hand, when loyalty disappears, the entry decision is almost solely driven by the market size, or in other words, rivals' customer base (black ribbon). This difference illustrates how capturing new smokers introduces a positive externality to the industry (for firms), which small products take advantage of by entering the market at higher rates. For BAT, this implies that offering its premium segment is easier (the participation rates when the locked-in customer base is 0) if loyalty is eliminated. The product is also less likely to be discontinued under this scenario. As a result, the product is offered with higher probability and reaches higher average market shares in steady-state (shift from the vertical black line to vertical blue lines).

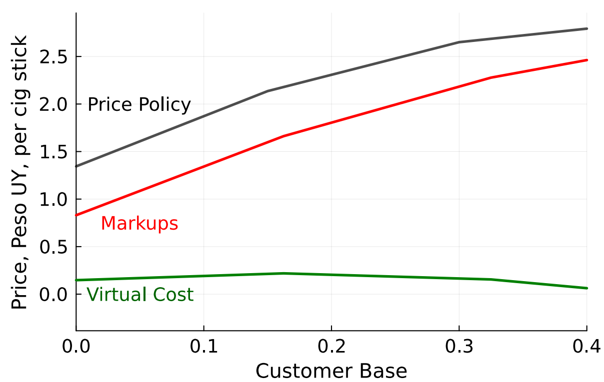
Countervailing Dynamic Effect: Virtual Costs If we had assumed that firms were not forward-looking, this increase in product availability and demand elasticity would have certainly increased consumption sharply. However, much of our previous analysis illustrated that firms consider the long-term implications of their actions. Once we account for firms' dynamic incentives, increasing demand elasticity and product availability is insufficient to induce higher long-run consumption. Firms also have less incentive to invest in attracting customers. This effect offsets, and sometimes even reverses the negative consequences of higher elasticity and product availability on consumption. Next, we use our estimates to illustrate and quantify this force.

In Equation 19, we revisit price first-order-condition decomposition to characterize firms' optimal pricing. Recall that firms' investing motives stem from the added long-term value of a customer ($\frac{\beta}{M}\frac{\partial EV_f}{\partial S_{ft}}$) and is equivalent to the negative of marginal cost, defining what we have called virtual costs. On the other hand, harvesting incentives encourage firms to mark up virtual costs based on the current customer base size $\left(\frac{S_{ft}}{\frac{\partial S_{ft}}{\partial p_{ft}}}\right)$.[34]

$$p_{ft} = \underbrace{\left(c_f - \frac{\beta}{M}\frac{\partial EV_f}{\partial S_{ft}}\right)}_{\text{Virtual Cost}} - \underbrace{\frac{S_{ft}}{\frac{\partial S_{ft}}{\partial p_{ft}}}}_{\text{Static Markup}} - \dots \tag{19}$$

Estimated price policies indicate that firms are willing to offer a low price when they do not have any customers and sharply increase them as the consumer base grows. Figure 12 presents the national firm flagship product's price policy as an example. The solid lines indicate the average price across rival customer bases, representing its own customer base on the horizontal axis. Moreover, we decompose prices in virtual costs and static markups.[35] The joint effect of investing and harvesting motives can explain, from a quantitative point of view, most of the shape of the optimal pricing function. According to our estimated model, the value an additional consumer has to the firm is high and mostly flat throughout the state space. Thus, the investing incentive uniformly reduces optimal prices (by lowering virtual costs). Additionally, the demand becomes increasingly more inelastic as the customer base grows. As a result, the harvesting incentives become more pronounced, leading to sharp price increases as firms expand their customer base.

Figure 12: Price Policy - Monte Paz, Flagship



Note: This figure represents the policies when marginal costs equal 1.8 U$. The shaded region indicates all the possible values the policy might take for a given size of the product's customer base. The policies are constructed by solving the model at the average parameters of the importance sampling distribution under the indicated levels of inertia.

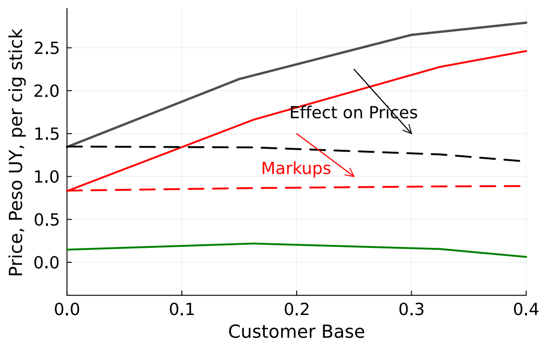
Lowering brand loyalty modifies equilibrium pricing policies in two ways. First, consumers become more price sensitive, and demand becomes less dependent on the consumption last period. Hence, firms' markups decrease and become less sensitive to the size of the customer base. This would substantially lower prices, as shown in Figure 13a, particularly for firms with a large equilibrium customer base (clockwise rotation). Price drops, in turn, would have increased consumption. This is precisely the argument that tobacco companies make against uniform packaging.

[34] Note that in this section we refer to markups as the unit margin over *virtual* costs.

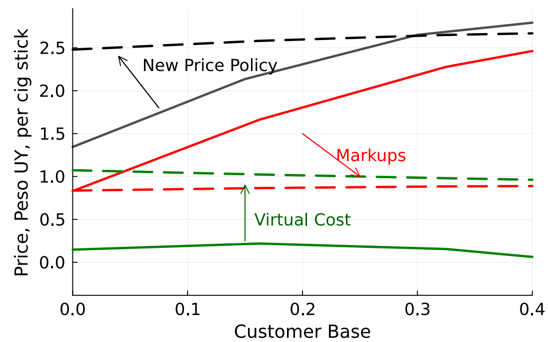
[35] Note the addition of these two components does not add up to the price policy because we are missing the strategic incentives of the firms and the pricing components that arise due to their multi-product nature.

Nevertheless, this is just half the story when firms are forward-looking, as in the Uruguayan tobacco industry. The long-term value of an additional customer to the firm decreases because consumers are significantly more likely to switch to other products in the next period. This is reflected in the increase of virtual costs as brand loyalty falls. The increase in virtual costs shifts up the policy, as illustrated in Figure 13b. The joint effect of virtual costs and static markups is to rotate the price policy clockwise and shift it up.

Figure 13: Price Decomposition - Monte Paz, Flagship



(a) Price Decomposition - Effect on Static Markups

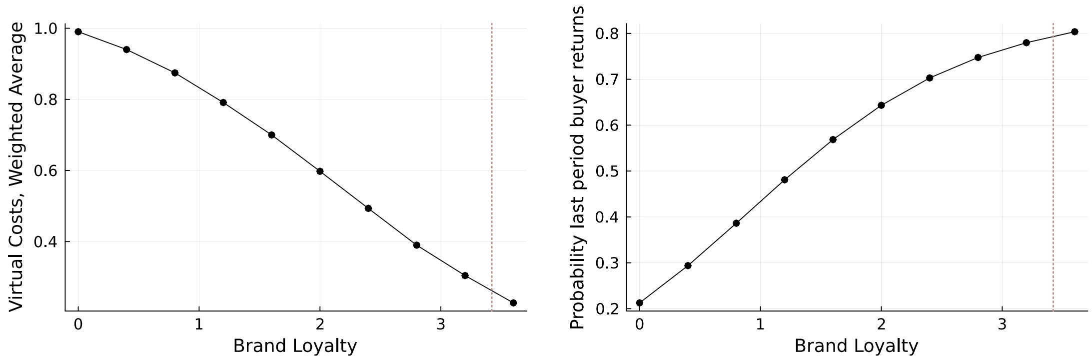


(b) Price Decomposition - Effect on Virtual Costs

Note: This figure represents the policies when marginal costs equal 1.8 U\$. The shaded region indicates all the possible values the policy might take for a given size of the product's customer base. The policies are constructed by solving the model at the average parameters of the importance sampling distribution under the indicated levels of inertia. Dashed vertical lines represent the average customer base for each level of inertia.

As a result, and according to our estimates, the long-run average virtual costs increase by a factor of four between our baseline loyalty estimates and when we eliminate it, as we represent in Figure 14a. The increase of virtual costs can be compared vis-a-vis with the decrease in the probability that a consumer who purchased a product returns the following period, which also decreases by a factor of four, as shown in Figure 14b. As we have mentioned, the probability that a customer returns is the critical determinant of firms' incentives to invest in attracting consumers, making these figures reassuring.

Figure 14: Long Run Industry Outcomes - Virtual Cost and Switching Behavior



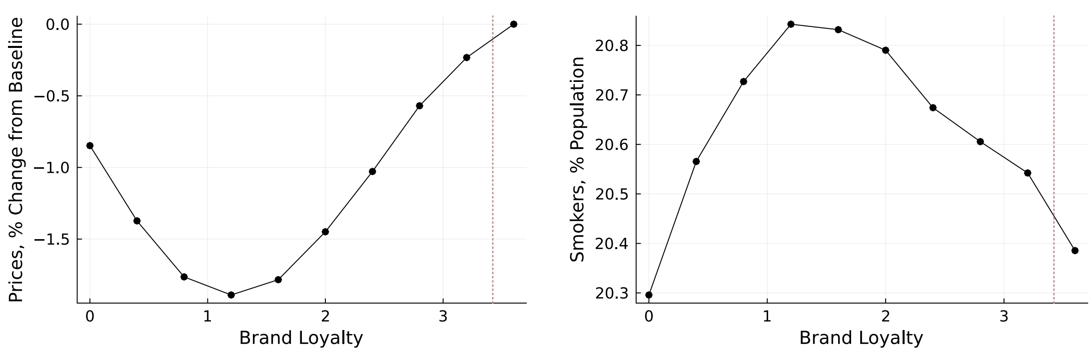
(a) Virtual costs

(b) Switching Behavior

Note: For each level of inertia, we solve for equilibrium policies for prices and market participation. Then, we simulate the industry evolution over 50 periods, replicated 2,500 times from a null industry scenario. The depicted results are the averages across time and simulations. The distribution of visited states is presented in Appendix G. Long-run average market shares are used as weights to aggregate across products. The vertical dotted brown line references estimated levels of inertia.

The counterbalancing forces between increasing elasticity (recall Figure 10a) and raising virtual cost lead to a small, non-monotonic effect on prices (see Figure 15a), which mirror the patterns in consumption (Figure 15b replicates figure Figure 9). The non-monotonic pattern between brand loyalty, prices, and consumption results from the initial market concentration, where a single product captures more than 50% of the market. As a result, initial drops in brand loyalty make the market leader's demand substantially more elastic without affecting the probability a customer returns as much, which leads to significant price drops. However, as brand loyalty decreases further, the market leader loses its dominant position, and the investing incentives dominate. We expand on this intuition in Appendix G.

Figure 15: Long Run Industry Outcomes - Prices and Consumption



(a) Average Price - % Change from Baseline

(b) National smoking rate

Note: For each level of inertia, we solve for equilibrium policies for prices and market participation. Then, we simulate the industry evolution over 50 periods, replicated 2,500 times from a null industry scenario. The depicted results are the averages across time and simulations. The distribution of visited states is presented in Appendix G. Long-run average market shares are used as weights to aggregate across products. The vertical dotted brown line references estimated levels of inertia.

The missing parts of prices in Equation 19 are firms' internalization of the effect that stealing consumers from rivals –and other products in their portfolio– has in its long-term value, and their incentives to induce exit or deter entry:

$$p_{ft} = \ldots \underbrace{\sum_{k:\mathbf{J}_{kt}=1,k\neq f} \frac{\frac{\partial S_{kt}}{\partial p_{ft}}}{\frac{\partial S_{ft}}{\partial p_{ft}}} \left(\frac{\beta}{M}\frac{\partial EV_f}{\partial S_k}\right)}_{\text{Dynamic Business Stealing}} + \underbrace{\frac{\beta}{M}\sum_{k:\mathbf{J}_{kt}=1}\left(\sum_{r=1,r\neq f}^{F}\left(E[V_f|\daleth_r=1]-E[V_f|\daleth_r=0]\right)\frac{\partial \sigma_r^{\phi}}{\partial S_{kt}}\right)\frac{\frac{\partial S_{kt}}{\partial p_{ft}}}{\frac{\partial S_{ft}}{\partial p_{ft}}}}_{\text{Entry Deterrence/Exit Inducing}} \tag{20}$$

Our estimated primitives suggest that firms lack significant incentives to induce rivals' exit or deter entry. Exploring this possibility is particularly relevant in our setting, considering that Philip Morris faced a lawsuit for predatory pricing due to its aggressive penetration pricing strategy. We capture predatory incentives through the entry-deterrence/exit-inducing term. While consumer inertia could introduce incentives to predate, the existing asymmetry among firms indicates that ousting rivals from the market is either exceedingly challenging or not lucrative. In other words, our analysis confirms that the aggressive pricing strategies observed in the data are consistent with investing in capturing new customers and not anti-competitive behavior.[36]

5.2 Addiction

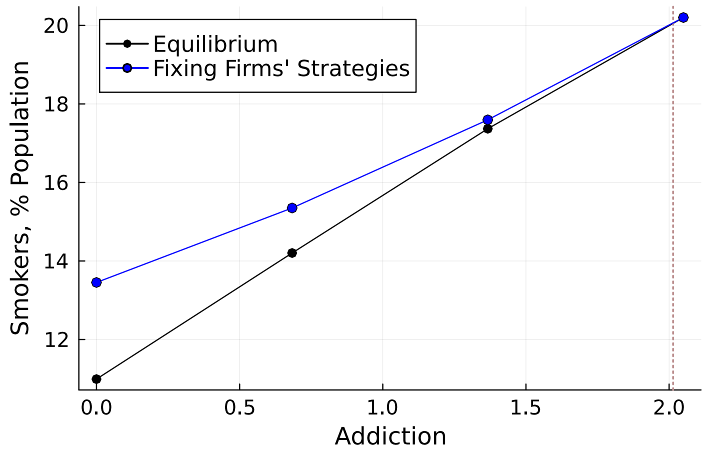
The previous result illustrates that decreasing incentives to lock customers in can reduce consumption even when consumers are substantially more elastic, do not value cigarettes less, and have access to more variety. In this section, we explore the effect of a policy that decreases consumer inertia *and* significantly reduces smokers' valuation for cigarettes, as is the case of reducing addiction.

Decreasing addiction is a critical area of concern for regulatory bodies. As we stressed in the motivation of this work, the FDA is actively looking to decrease the nicotine content of cigarettes to reduce addiction. In this case, the policy directly impacts consumers' valuation of cigarettes by not adding any utility from smoking due to past consumption. We first evaluate the impact of the policy, holding firms' strategies fixed, and then assess its equilibrium effects.

If eliminating nicotine eradicates dependence (i.e., we shift the addiction parameter to 0.0), and firms hold their strategies fixed, the national smoking rate would decrease 30 % to slightly below 14 % of the population. Interestingly, when firms adjust their strategies, they reinforce the effect, reducing the smoking rate up to 25% more, as shown in Figure 16.

[36]On the contrary, firms appear more inclined towards softening competition to avoid potential reprisals that could spark fiercer competition in subsequent periods.Figure G.9 quantifies and contrasts the dynamic business stealing effects with the exit-inducing/entry deterrence motives. This "cooperative" feature distinguishes competition under inertia from other dynamic pricing models, such as learning-by-doing [Cabral and Riordan, 1994, Besanko et al., 2014] or network externalities [Farrell and Katz, 2005], where firms typically exhibit a more aggressive stance to undercut rivals and secure a favorable competitive position in the future.

Figure 16: National smoking rate under counterfactual addiction.

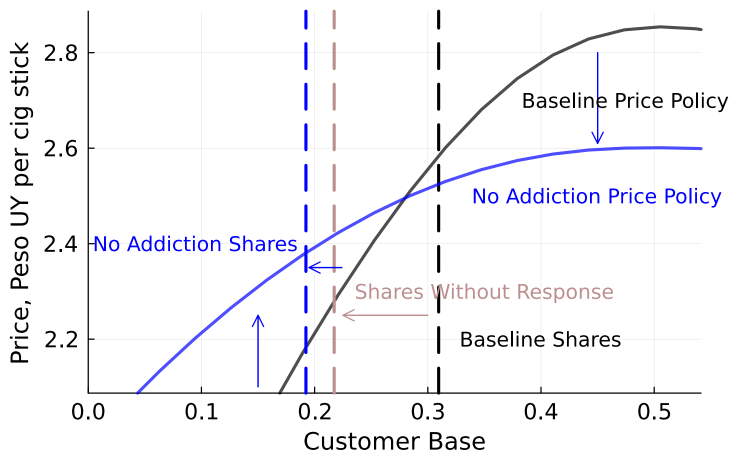


Note: For each level of inertia, we solve for equilibrium policies for prices and market participation. Then, we simulate the industry evolution over 50 periods, replicated 2,500 times from a null industry scenario. The depicted results are the averages across time and simulations. For the results where we fix firms' strategies, we solve the equilibrium at the baseline level of inertia and then simulate the economy modifying consumer preferences. The distribution of visited states is presented in Appendix G. The average smoking rates are computed assuming that the available market size represents 35.6 % of the population, which was the average smoking rate in Uruguay in 2000. The vertical dotted brown line references estimated levels of inertia.

To understand why consumption decreases more in equilibrium, it is essential to remember that firms' strategies determine a price *function*. When the firm has a small customer base, it is willing to offer a low price to attract new customers. As the customer base grows, the firm increases its price to exploit the locked-in customers. The direct effect of reducing addiction is to decrease smokers' demand for cigarettes. If firms do not adjust their strategies, their price response is to sharply lower prices to recover part of their lost consumer base. However, this is not the optimal response. Firms recognize that they are less able to retain customers because addiction is lower. Therefore, the policy discourages firms from investing in turning individuals into smokers. Overall, this change in strategies induces further decreases in smoking rates. Next, we describe the mechanisms behind this result in detail, using the estimated price policy of the national firm flagship product as an example.

The direct effect of lowering addiction is to shift smokers' demand for cigarettes down. If firms do not adjust their strategies, long-run equilibrium consumption drops and firms decrease prices significantly. At the pre-policy investing-harvesting level (without adjusting to the new context), firms would reduce prices aggressively to expand their customer base because they incorrectly believe they can lock customers in once attached to the product. In Figure 17, we illustrate the long-run outcomes in this non-equilibrium case by the shift from the intersection between the steady state customer base and the equilibrium pre-policy price function to the intersection between steady state customer under new consumer preferences holding pre-policy optimal pricing function.

Figure 17: Price Policy - Monte Paz, Flagship, Addiction



Note: This figure represents the policies when marginal costs equal 1.8 U$. The shaded region indicates all the possible values the policy might take for a given size of the product's customer base. The policies are constructed by solving the model at the average parameters of the importance sampling distribution under the indicated levels of inertia. Dashed lines represent the average customer base for each level of inertia. The pink vertical dashed line represents the customer base when addiction is eliminated, but firms continue to play the strategies at the baseline addiction level (blue policies)

However, equilibrium strategies change as a response to lower addiction. Firms understand that they cannot retain consumers as efficiently as before. Hence, even though the demand for cigarettes decreased significantly, the optimal price function shifts up (and rotates clockwise), reflecting an increase in virtual costs. Thus, at the customer base size that would arise if firms did not adjust their strategies (vertical pink line), firms choose not to price as aggressively, following the pricing function in blue. Figure 17 reflects this adjustment, shifting prices from the intersection of the pink vertical line with pre-policy prices (black curve) to the intersection with the post-policy prices (blue curve). This softening in firms' pricing strategies induces further contractions of the average long-run customer base, which reduces prices further in equilibrium (intersection of blue curve and vertical dashed line).

Figure 17 illustrates that, at the average customer base in the new long-run steady state, prices are lower than before lowering addiction. Still, they are higher than if firms had not adjusted their strategies to account for the new level of smokers' addiction. Figure G.15 shows that average prices, in the long run, drop up to 10% when we eliminate addiction, while the number of products slightly decreases.

Our analysis shows that considering firms' long-term incentives has crucial implications for policy analysis in the tobacco industry. We have argued that once we account for firms' incentives to decrease prices to lock consumers into their products, reducing brand loyalty is unlikely to affect consumption negatively. This occurs although we have assumed customers continue to value cigarettes as much as before the policy, demand elasticity increases up to three times, and consumers have access to more variety. Moreover, we showed that firms' responses to lower addiction reinforce the effect of the policy because they stop investing in turning individuals into smokers.

5.3 Taxes

Our previous results suggest that reducing inertia in tobacco (or other markets) can be a valuable tool to reduce smoking rates without substantially increasing the burden on smokers. This result contributes to the heated discussion among regulators about the limits to discourage consumption of sin goods such as tobacco, alcohol, and sugar by making them less affordable. In particular, there is strong evidence that discouraging sin goods consumption through taxation has adverse distributional effects [Conlon et al., 2022]. Moreover, the excessive use of taxes faces other economic and political challenges, such as lowering tax revenue and substitution towards black markets.

In this section, we briefly explore how different combinations of policies that tax tobacco and reduce addiction and brand loyalty perform. First, we establish a target smoking rate of 10%. Then, we find the tax that takes the smoking rate to the target for each counterfactual level of inertia or addiction. We then compare the long-term prices, unit margins, and revenue collection generated in equilibrium by each policy combination.[37]

Table 4 shows the results of this exercise. We observe that policies that reduce inertia, both brand loyalty and addiction, can reduce smoking rates to 10% of the population without increasing the burden on smokers as much. In particular, eliminating brand loyalty reduces the equilibrium price by 1.5%. By limiting firms' incentives to capture new consumers, they are less tempted to turn individuals into smokers, and the increase in prices needed to decrease smoking rates is not as significant. Note, however, that the government collects less tax revenue, and firms charge higher unit margins than if we take smoking rates to 10% without eliminating inertia. The latter results from firms adjusting their optimal pass-through to changes in consumer inertia.[38]

Table 4: Equilibrium price, tax revenue, and unit margins at 10 % smoking rate.

	Price	Unit Margin	Revenue
Tax only	2.94	0.8	75.41
Tax + No Loyalty	2.9	0.87	73.84
	(-1.4%)	(9.73%)	(-2.09%)
Tax + No Addiction	2.37	0.65	58.01
	(-19.47%)	(-18.23%)	(-23.07%)

Eliminating addiction reduces the equilibrium price by 19.5%. This is because the tax needed to reduce

[37] For simplicity, we assume firms offer only their main products (Monte Paz Flagship, Philip Morris Flagship, and BAT Standard) and shut down the entry/exit dimension

[38] Without inertia, tax pass-through in imperfectly competitive makers hinges on the curvature of demand, as outlined by Anderson et al. [2001], Miravete et al. [2018]. The presence of consumer inertia alters this dynamic in two ways. Firstly, the curvature of demand changes as the customer base expands, just as a larger base of consumers creates more incentives to harvest–see Equation 19. Secondly, tax hikes diminish the additional long-term value a new customer brings to the company. This, in turn, reduces firms' motivation to invest in broadening their customer base. These forces determine the shape of the pass-through function. At our estimated levels of inertia, the pass-through is decreasing in the size of the customer base. This results from taxes lowering firms' incentives to invest in expanding their customer base. However, the reduction in equilibrium in the customer base introduces a wedge between the short-term and long-term pass-through. In particular, firms tend to "overshoot" the taxes in the short term and slowly decrease prices as the locked-in customer base shrinks.

smoking rates to 10% is much lower than in the baseline. Moreover, firms' incentives to invest in attracting new consumers are lower, which reduces the price even further. However, the government collects less tax revenue, and firms charge lower unit margins than if we take smoking rates to 10% without eliminating addiction.

6 Conclusions

In summary, addressing and mitigating consumer inertia is instrumental in curtailing smoking habits. While decreasing brand loyalty can increase consumption slightly in the worst-case scenarios, substantially lessening inertia leads to lower investments to attract new smokers. This change in firms' strategies allows regulators to decrease smoking rates without passing as much of a cost burden onto consumers.

Our results also provide rich economic intuition to analyze other markets where consumer inertia is relevant. We emphasize that firms' optimal balance between investing and harvesting impacts more than just the price level. We illustrate how it can also influence overall consumption (beyond its effect on long-term prices), firms' optimal product assortment, and their response to taxes.

Finally, we have argued that incorporating firm behavior can aid in identifying consumer inertia. Although our methodological approach enables the empirical analysis of the industry, it still needs to be more flexible to be used in conjunction with consumer choices to identify state dependence. Designing the empirical tools to implement this strategy is a promising avenue for future research.

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A Appendix: Additional Modeling Details

A.1 Equilibrium Definition

Constructing expected customer base for non-tracked products Let $\Omega(\gimel)$ be a random variable representing the shares of the MPE's recurrent class of the pricing game without entry and exit under choice set $\gimel$. Moreover, let $pr(\Omega(\gimel)|I_f)$ be its distribution of market shares conditional on firm f information set (note that $\mathbb{J} \in I_f$).

Then, for a given realization ω_f from the distribution $pr(\Omega(\gimel)|I_f)$ firms can construct the vector of customer bases as

$$S^{e(f)}_{k,t-1}(\omega_f, I_f) = \begin{cases} S^f_{k,t-1} & k \in T^f \\ \omega_k | I_f & \text{otherwise} \end{cases} \tag{21}$$

where the ω_f argument reflects that $S^{e(f)}_{k,t-1}(.,I_f)$ is a random variable, whose distribution is determined by $pr(\Omega(\gimel)|I_f)$. The key limitation of this approach is that the private information component of I_f, $(S^f_{t-1}, \bar{S}^f_{t-1})$ might not be observed in the support of $\Omega(\mathbb{J})$ because it is a continuous variable. Hence, we perform simple linear interpolations to construct firms beliefs about the vector of customer bases, conditional on their information set I_f.

Then, firms can leverage this information to construct a distribution of rivals information sets $pr(I_{-f}|I_f)$ simply aggregating rivals tracked and non-tracked shares according to $S^{e(f)}_{k,t-1}$. Let ζ_f be a realization of $pr(I_{-f}|I_f)$, then firms evaluate rivals' actual strategies at their perceived information sets: $\sigma_{-f}(\zeta_f)$.

Constructing shares without observing consumer-type/past-choice shares. For a given vector of prices $p_t = (\sigma^p_f(I_f), \sigma^p_{-f}(\zeta_f))$, choice set $\mathbb{J}$, and consumer preferences μ^D, we can compute the probability that consumer-type n, previously consuming product k, chooses product j. However, constructing the market share of product j at time t requires knowledge on the joint distribution of customer bases and product types, which firms do not possess. We leverage our assumption on the conditional distribution of types conditional on previous consumption $w[n|k]$ to construct market shares.

$$S^{e(f)}_{jt}(\omega_f, \zeta_f, I_f; \sigma) = \sum_{k=1}^{F} \sum_{n=1}^{N} S_{knjt}(p_{jt}, \mathbb{J}; \sigma_{-f}(\zeta_t), \mu^D) S^{e(f)}_{k,t-1}(\omega_f, I_f) w[n|k]$$

Note that using this information firms can construct the distribution of next period tracked shares and their aggregates, which defines the Markov process on information sets: $pr(I'_f|I_f, \sigma)$.

Expected Payoff Moreover, firms can construct the expected payoff and value functions. For the per-period profits, we write payoffs as

$$\pi^{e(f)}(I_f;\sigma) = M \times \int \left\{ S^{e(f)}(\omega_f, \zeta_f, I_f; \sigma) \times (\sigma_f^p - c_f) - E_\Theta \left[\Theta_f \times 1\{\Theta_f \leq \bar{\Theta}(I_f, \sigma_{-f}^\phi(\zeta_f))\} \right] \right\} pr(\zeta_f|I_f) pr(\omega_f|I_f) \tag{22}$$

A.2 Dynamic model for multi-product firms

The only relevant difference between the dynamic model for multi-product and single-product firms is how they choose product portfolios, as extending pricing decisions to the multi-product case is straightforward.

In the single firm case, optimal participation decisions are characterized by a threshold rule. Thus, participation probabilities characterize the entire participation strategy without loss of information. On the other hand, if multi-product firms observe the realization of fixed costs for all products simultaneously, they must consider the probability of each possible bundle, which is not a threshold strategy rule. In principle, we could solve for each bundle's equilibrium probabilities as in Draganska et al. [2009]

Let $\daleth_f$ be one possible bundle offered by firm f at t. Then, taking into consideration that shocks to fixed costs are private information of the firms, the probability of offering this bundle –omitting all other states– is given by

$$Pr(\daleth_f) = \int 1 \left\{ \daleth_f = \text{argmax}_J \left(\beta \int_{\daleth_{-f}} V(J, \daleth_{-f}) dF(\daleth_{-f}|\sigma_{-f}^\phi) - \sum_{k:J_k=1} \Theta_k \right) \right\}$$

The indicator function $1\left\{ \daleth_f = \text{argmax}_J \left(\beta \int_{\daleth_{-f}} V(J, \daleth_{-f}) dF(\daleth_{-f}|\sigma_{-f}^\phi) - \sum_{k:J_k=1} \Theta_k \right) \right\}$ defines an area of integration $A^{\daleth_f}$. This area is the region of realizations of $\Theta_f \in \mathbb{R}^K$ over which offering $\daleth_f$ is optimal. Moreover, we can define product-specific areas of integration for each bundle. That is, the area of integration under which product $k(f)$ is offered under state is $A_{k(f)} = \{\Theta_f \in \cup_{\{\daleth_f : \daleth_{fk}=1\}} A_k^{\mathbb{J}_f}\}$. Hence, we can re-express $\chi_{k(f)}(\Theta_f) = 1\{\Theta_f \in A_{k(f)}\}$. Note that $\chi_k(f)(\Theta_f)$ depends on the entire vector of fixed cost shocks of firm f but not on shocks of other firms since these are private still information.

Then, the value of firm f before participation choices are made is

$$U_f(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}; \sigma) = -E\left[\sum \Theta_{k(f)} 1\{\Theta_f \in A_{k(f)}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \sigma_{-f}^\phi)\} \right] + \beta E[V(S_t, \daleth, c_{t+1}, \delta_{t+1})|\sigma^\phi]$$

However, working with the derivatives of such expectations with respect to prices would be complex. In particular, it would make the solution to the pricing problem significantly more involved. We simplify the problem by assuming fixed cost shocks are also private information within the firm. That is, the departments in charge of deciding on the participation of different products do not need to communicate with each other. Nevertheless, they optimize considering the profits of the whole firm. Hence, possible cannibalization effects are still accounted for.

A.3 Three different model interpretations

The model can be interpreted differently depending on how we set the dynamic components of utility. In the main text, we assume that repeated purchases provide an additional utility to consumers, both continuing to smoke and repeating the exact same product choice:

$$
\begin{aligned}
u_{ijmt}(z) &= \delta_{jtm} + \sum_r \sum_k (D_i^r X_j^k)\gamma^{kr} + \eta_0 1\{z \neq 0\} + \eta_1\{z = j\} + \varepsilon_{ijmt} \quad \text{if } j \neq 0 \\
u_{i0mt}(z) &= \varepsilon_{i0mt} \quad \text{otherwise}
\end{aligned}
\tag{23}
$$

Nonetheless, the model admit different interpretations. For instance, we could assume that consumers do not get an additional utility from repeating the exact same product choice, but incur a cost when switching. In that case, we could re-write consumers utility as

$$
\begin{aligned}
u_{ijtm}(z) &= \tilde{\delta}_{jtm} + \sum_r \sum_k (D_i^r X_j^k)\gamma^{kr} - \eta_0 1\{z = 0\} - \eta_1\{z \neq j\} + \varepsilon_{ijtm} \quad \text{if } j \neq 0 \\
u_{i0mt}(z) &= \varepsilon_{i0st} \quad \text{otherwise}
\end{aligned}
\tag{24}
$$

where $\tilde{\delta}_{jtm} = \delta_{jtm} + \eta_0 + \eta_1$

In this formulation of the model, consumers pay a switching cost to change product or leave the market, and non-smokers find cigarettes less appealing than smokers. Regarding the latter interpretation, we could have also assumed that it is not the smokers that find cigarettes less appealing, but smokers who find it hard to quit. In that case, the normalization of the outside option would be different:

$$
\begin{aligned}
u_{ijtm}(z) &= \bar{\delta}_{jtm} + \sum_r \sum_k (D_i^r X_j^k)\gamma^{kr} - \eta_1\{z \neq j\} + \varepsilon_{ijtm} \quad \text{if } j \neq 0 \\
u_{i0mt}(z) &= -\eta_0 1\{z \neq 0\} + \varepsilon_{i0st} \quad \text{otherwise}
\end{aligned}
\tag{25}
$$

with $\bar{\delta}_{jtm} = \delta_{jtm} + \eta_1$.

Although these specifications are analogous for estimation purposes, they imply different counterfactuals. In each case, eliminating inertia would have different implications on consumption because it has a simultaneous effect on the truly inertial component and the mean valuation of products. Hence, in our counterfactuals we isolate the effect of inertia from the mean valuation component. To that end, for each counterfactual value of consumer inertia η^c, we compute a compensating mean utility, δ^c. This compensating utility makes the market shares at the optimal prices without inertia and δ equal to the shares at the same prices but with consumer inertia at η.

A.4 Representing the state space with inside goods' market shares.

Demand depends on lagged market shares according to equation Section A.4. At the national level, we can summarize this dependence as

$$S_j(s) = \lambda \sum_{k \in \{0,\ldots,N\}} s_k S_{jk} + (1-\lambda) S_{j0}$$

In principle, we could keep track of all market shares. However, we can use the market shares of only the inside goods as states. Next, we show that both approaches are equivalent up to an scaling factor. That is, if we include the outside option as a state then pricing depends on $\frac{\partial V_f(\tilde{s}, s_0)}{\partial s_j} - \frac{\partial V_f(\tilde{s}, s_0)}{\partial s_0}$. Instead, if it is not included it depends directly on $\frac{\partial \tilde{V}_f(\tilde{s})}{\partial s_j}$. Nevertheless, it is easy to show that $\frac{\partial V_f(\tilde{s}, s_0)}{\partial s_j} - \frac{\partial V_f(\tilde{s}, s_0)}{\partial s_0} = \frac{\partial \tilde{V}_f(\tilde{s})}{\partial s_j}$. Therefore, when we restrict the state space to the inside goods, the correct interpretation of the score of value functions should be the differential gain with respect to an increase in the outside option.

We can illustrate the previous observation in the case of a multi-product monopolist. Let $1,2$ be two products produced by the same firm. Then, without participation choices the value function of the firm, taking the share of the outside option as a state is

$$V(s_0, s_1, s_2) = \max_{p_1, p_2} M \times (S_1(s,p)(p_1 - c_1) + S_2(s,p)(p_2 - c_2)) + \beta V(S_0(s,p), S_1(s,p), S_2(s,p))$$

Price FOC are

$$p_j: \quad \frac{\partial \pi_f}{\partial p_j} + \beta \left\{ \frac{\partial V(S)}{\partial S_0} \frac{S_0}{\partial p_j} + \frac{\partial V(S)}{\partial S_1} \frac{S_1}{\partial p_j} + \frac{\partial V(S)}{\partial S_2} \frac{S_2}{\partial p_j} \right\} = 0$$
$$p_j: \quad \frac{\partial \pi_f}{\partial p_j} + \beta \left\{ \left(\frac{\partial V(S)}{\partial S_1} - \frac{\partial V(S)}{\partial S_0} \right) \frac{S_1}{\partial p_j} + \left(\frac{\partial V(S)}{\partial S_2} - \frac{\partial V(S)}{\partial S_0} \right) \frac{S_2}{\partial p_j} \right\} = 0$$

Moreover, we can apply the envelope theorem to obtain a measure of the gradient of the value function with respect to lagged market shares.

$$\begin{aligned}
\frac{\partial V(s)}{\partial s_0} &= M \times (\lambda S_{10}(p_1 - c1) + \lambda S_{20}(p_2 - c2)) + \beta \left\{ \frac{\partial V(S)}{\partial S_0} \lambda S_{00} + \frac{\partial V(S)}{\partial S_1} \lambda S_{10} + \frac{\partial V(S)}{\partial S_2} \lambda S_{20} \right\} \\
\frac{\partial V(s)}{\partial s_1} &= M \times (\lambda S_{11}(p_1 - c1) + \lambda S_{21}(p_2 - c2)) + \beta \left\{ \frac{\partial V(S)}{\partial S_0} \lambda S_{01} + \frac{\partial V(S)}{\partial S_1} \lambda S_{11} + \frac{\partial V(S)}{\partial S_2} \lambda S_{21} \right\} \\
\frac{\partial V(s)}{\partial s_2} &= M \times (\lambda S_{12}(p_1 - c1) + \lambda S_{22}(p_2 - c2)) + \beta \left\{ \frac{\partial V(S)}{\partial S_0} \lambda S_{02} + \frac{\partial V(S)}{\partial S_1} \lambda S_{12} + \frac{\partial V(S)}{\partial S_2} \lambda S_{22} \right\}
\end{aligned} \tag{26}$$

Next, we can solve an equivalent problem but restricting the state space to s_1, s_2. Let $\bar{s}$ be the vector of inside goods' market shares, then we can modify the market share function -abusing notation- as

$$S_j(\tilde{s}) = \lambda \sum_{k\in\{0,1,..,N\}} s_k S_{jk} + (1-\lambda)S_{j0} = \lambda \sum_{k\in\{1,..,N\}} s_k S_{jk} + \lambda s_0 S_{j0} + (1-\lambda)S_{j0} = \lambda \sum_{k\in\{1,..,N\}} s_k(S_{jk} - S_{j0}) + S_{j0}$$

Let $\tilde{V}$ be the value function defined over $\tilde{s}$, instead of V, which is defined over s. Then, price FOC are simply

$$p_j: \quad \frac{\partial \pi_f}{\partial p_j} + \beta \left\{ \frac{\partial \tilde{V}(\tilde{S})}{\partial S_1} \frac{S_1}{\partial p_j} + \frac{\partial \tilde{V}(\tilde{S})}{\partial S_2} \frac{S_2}{\partial p_j} \right\} = 0$$

Again, we can obtain the gradient of $\tilde{V}$ with respect the states $\tilde{s}$ using the envelope theorem

$$\begin{aligned}
\frac{\partial \tilde{V}(\tilde{s})}{\partial s_1} &= M \times (\lambda(S_{11} - S_{10})(p_1 - c1) + \lambda(S_{21} - S_{20})(p_2 - c2)) + \beta \left\{ \frac{\partial \tilde{V}(\tilde{S})}{\partial S_1} \lambda(S_{11} - S_{10}) + \frac{\partial \tilde{V}(\tilde{S})}{\partial S_2} \lambda(S_{21} - S_{20}) \right\} \\
\frac{\partial \tilde{V}(\tilde{s})}{\partial s_2} &= M \times (\lambda(S_{12} - S_{10})(p_1 - c1) + \lambda(S_{22} - S_{20})(p_2 - c2)) + \beta \left\{ \frac{\partial \tilde{V}(\tilde{S})}{\partial S_1} \lambda(S_{12} - S_{10}) + \frac{\partial \tilde{V}(\tilde{S})}{\partial S_2} \lambda(S_{22} - S_{20}) \right\}
\end{aligned} \tag{27}$$

Finally, subtracting the first equation to the other two in Equation 26 and operating we get

$$\begin{aligned}
&\frac{\partial V(s)}{\partial s_1} - \frac{\partial V(s)}{\partial s_0} = M \times (\lambda(S_{11} - S_{10})(p_1 - c1) + \lambda(S_{21} - S_{20})(p_2 - c2)) + \\
&\beta \left\{ (\frac{\partial V(S)}{\partial S_1} - \frac{\partial V(S)}{\partial S_0})\lambda(S_{11} - S_{10}) + (\frac{\partial V(S)}{\partial S_2} - \frac{\partial V(S)}{\partial S_0})\lambda(S_{21} - S_{20}) + \frac{\partial V(S)}{\partial S_0}\lambda(S_{01} - S_{00} + S_{11} - S_{10} + S_{21} - S_{20}) \right\} \\
&\frac{\partial V(s)}{\partial s_2} - \frac{\partial V(s)}{\partial s_0} = M \times (\lambda(S_{12} - S_{10})(p_1 - c1) + \lambda(S_{22} - S_{20})(p_2 - c2)) + \\
&\beta \left\{ (\frac{\partial V(S)}{\partial S_1} - \frac{\partial V(S)}{\partial S_0})\lambda(S_{12} - S_{10}) + (\frac{\partial V(S)}{\partial S_2} - \frac{\partial V(S)}{\partial S_0})\lambda(S_{22} - S_{20}) + \frac{\partial V(S)}{\partial S_0}\lambda(S_{02} - S_{00} + S_{12} - S_{10} + S_{22} - S_{20}) \right\}
\end{aligned}$$

and after canceling the last terms -$(S_{02} - S_{00} + S_{12} - S_{10} + S_{22} - S_{20}) = 0$, we see that we have a system that is exactly equivalent to Equation 27.

A.4.1 Participation Problem under Exponentially Distributed Fixed Costs

As shown by Doraszelski and Satterthwaite [2010] the participation problem can be expressed in terms of participation thresholds, or participation probabilities. The latter representation usually turns out to be more useful. Thus, we can express the participation problem as

$$\max_{\phi_j} -E[\Theta_j \times 1\{\Theta_j \leq F^{-1}(\phi_j)\}] + \beta E[V_f(\daleth)]$$

Now, assuming fixed costs are exponentially distributed, we have

$$E[\Theta_f \times 1\{\Theta_f \le F^{-1}(\phi_f)\}] = \phi\mu - (1-\phi)F^{-1}(\phi_f)$$

where μ is the unconditional mean of the fixed cost distribution. Moreover,

$$F^{-1}(\phi_f) = -\mu \times log(1-\phi_j)$$

FOC of the participation problem boil down to

$$F_j^\phi = \beta\left(E[V_f|\beth_r = 1] - E[V_f|\beth_r = 0]\right) + \mu log(1-\phi_j) = 0$$

Therefore, applying the implicit function theorem, it is easy to see that

$$\nabla\phi_s = -(\nabla F_\phi^\phi)^{-1}\nabla F_s^\phi \tag{28}$$

Furthermore, these Jacobian matrices are easy to characterize and derive in closed form. The diagonal of $\frac{\partial\phi}{\partial s}$ is determined by the effect of higher participation probabilities on participation costs, while off diagonal effects' are influenced by how rivals participation influence participation threshold. Thus,

$$\frac{\partial F_j^\phi}{\partial\phi_k} = \begin{cases} -\frac{\mu}{1-\phi_j} & \text{if } j = k \\ \beta\left\{\left(E[V_f|\beth_j = 1, \beth_k = 1] - E[V_f|\beth_j = 0, \beth_k = 1]\right) - \left(E[V_f|\beth_j = 1, \beth_k = 0] - E[V_f|\beth_j = 0, \beth_k = 0]\right)\right\} & \text{if } j \ne k \end{cases}$$

On the other hand, ∇F_s^ϕ is simply the gradient of the participation threshold with respect to loyal bases.

A.5 Markup Decomposition

In Equation 13 we show that firms set markups over opportunity costs following the inverse elasticity pricing rule. We also noted, that this markup could either increase or decrease with inertia. In this section we decompose firms' elasticity of demand into two components: the elasticity of demand from locked-in consumers and the elasticity from non-affilatied (to their product) customers. The weights are the proportion of each group of buyers in the firm's overall share.

$$\frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = \sum_k \left(\frac{w(k)s_j(k)}{s_j}\right)\left\{\frac{\partial s_j(k)}{\partial p_j}\frac{p_j}{s_j(k)}\right\}$$

The first term in the summand over k is the proportion of consumers of product j that were previously consuming good k. The second term is the group k's specific elasticity of demand. Furthermore, it is useful to think of this decomposition as a weighted average between the elasticity from locked-in consumers and non-affiliated customers. Letting $\tilde{w}_j(k)$ represent the proportion of consumers of good j that were patronizing product k, and $\varepsilon_j(k)$ the group specific elasticity of product k, we can write the decomposition as

$$\varepsilon_j = \tilde{w}_j(j)\varepsilon_j(j) + \sum_{k \neq j} \tilde{w}_j(k)\varepsilon_j(k)$$

As consumer inertia increases, $\tilde{w}_j(j)$ increases and $\varepsilon_j(j)$ becomes lower in absolute value, which makes the overall demand more inelastic. However, $\varepsilon_j(k)$ increases in absolute value with the size of inertia. If the relative weight of non-affiliated consumers in total demand is large, the latter effect might dominate, making demand more elastic.

B Appendix: Market Description

B.1 Data Summary Statistics

Figure B.1: Aggregate National Sales and Sample Aggregate Sales

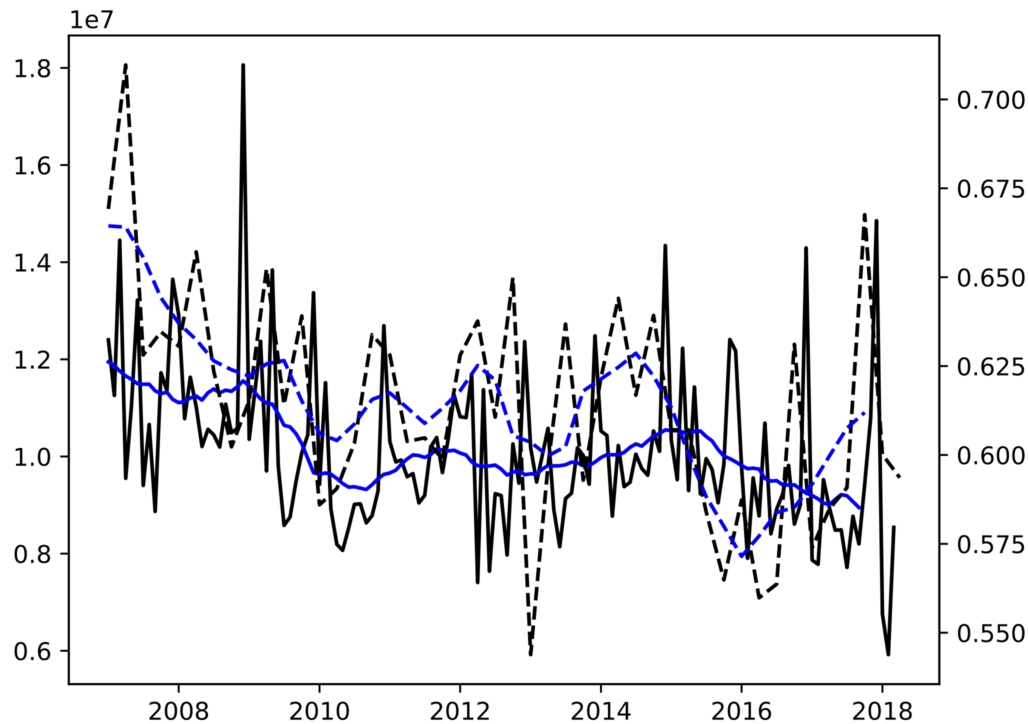


Table B.1: Data Summary Statistics

	All	Final Sample
Markets	71	38
Stores	3601	93
Observations	130880	12422

	All	Final Sample
Individuals	2208	1305
Observations	4978	2850

B.2 Market Segmentation

Our supply-side model cannot accommodate many products within a firm portfolio. Next, we show that there are well-defined market segments over which consumers have similar preferences, firms price uniformly, and such that all products within it are introduced/retired at the same time. This allows us to reduce the number of products in the choice set without losing much information. Next, we describe what are the main cigarettes segments from the perspective of consumers in the Uruguayan cigarette market. Then we show that firms set almost identical prices for all products within a segment. In turn, we argue that following product or segment shares provide almost as much information. Finally, we show that the entry and exit of products coincide with the evolution of these market segments.

B.2.1 Vertical and Horizontal Differentiation

There are eight clearly differentiated product segments. First, we differentiate between four types of cigarettes: flagship products (or leader products), other products with normal levels of tar, light cigarettes (low in tar), and products with special characteristics such as slightly longer than normal, slimmer, no filter, etc. Flagship products are the market best-selling product of each firm and are generally associated with brands that have a long tradition in the Uruguayan market, such as Nevada, Coronado (Monte Paz), Fiesta and Marlboro (Philip Morris), Pall Mall (BAT). Light products might share brand names with the flagship products but are low in tar and generally less popular. Finally, other regular products are "common" cigarettes, with similar levels of tar as flagship products, but that do not belong to a leader brand.

Within each of these categories, there are two types of vertical "qualities": standard and premium. The low-cost segment, which is common in other countries, did not develop in Uruguay. Table B.2 shows market shares across these dimensions and firms. The premium segment is small, and only BAT and Philip Morris sell premium cigarettes. However, these segments are not completely isolated markets. There exists non-trivial substitution between premium-light categories–see Table B.4.

Table B.2: Market Share by Segment and Firm.

	Leader			Other Regular			Light			Specials		
	MP	BAT	PM	MP	BAT	PM	MP	BAT	PM	MP	BAT	PM
Standard	0.559	0.050	0.133	0.024	-	0.011	0.073	-	0.022	0.002	-	-
Premium	-	0.018	0.054	-	-	-	-	0.009	0.035	-	-	-

B.2.2 Price Evolution by Segment

Firms price products within each one of these categories uniformly. In some cases, prices are identical across products within a segment. For instance, the flagship and light products within the standard segment (see Monte Paz' Nevada Filtro and Nevada Blanco-California prices). Figure B.2 shows prices for premium products. We see that all products within a firm-premium category have similar prices (it is even hard to distinguish different lines). The evolution of prices in the standard quality category is slightly more complicated. In particular, there are two price levels in this segment. The most common price is the higher one. So there is not exactly one price for medium products. However, the bulk of the segment shares are determined by one price per firm.

Figure B.2: High Segment Prices.

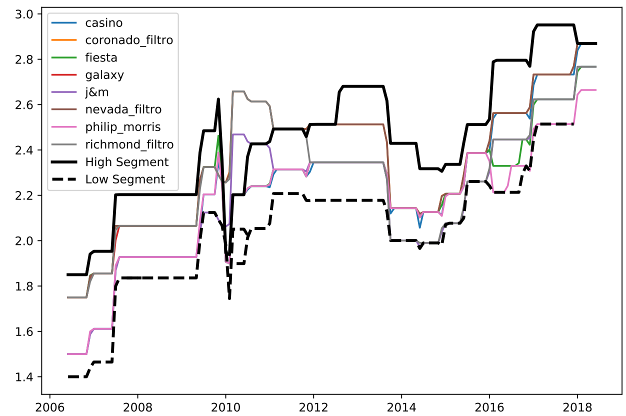
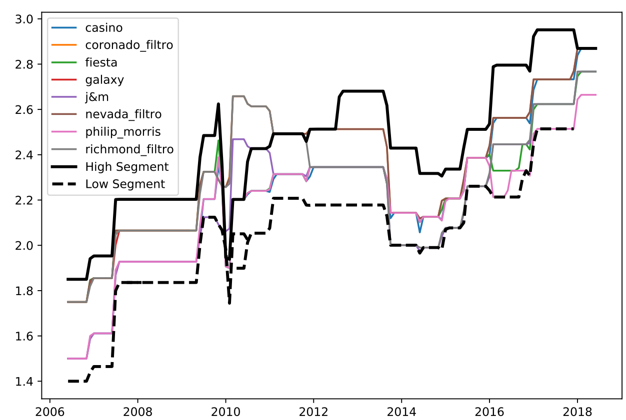


Figure B.3: Medium Segment Prices.



Overall, this evidence suggests that firms set prices uniformly across products within segments and sometimes across segments. Next, we show that if firms set uniform prices for all products within a segment and consumers value these products, then tracking individual-level products or segment aggregates should generate similar strategies and equilibrium outcomes.

B.2.3 Error Bounds

Suppose there are four products and two firms, each owning two. Assume further that firms price both products uniformly. Then, obtaining an approximation of the total demand of each firm is enough to obtain firms' profits. Observe that we can write product j shares as

$$
\begin{aligned}
S_{jt}(S_{t-1};p_t) &= \sum_{k=1}^{4} S_{jkt}(p_t)S_{k,t-1} \\
&= (S_{j1t}+S_{j2t})\frac{S_{1,t-1}+S_{2,t-1}}{2} + (S_{j3t}+S_{j4t})\frac{S_{3,t-1}+S_{4,t-1}}{2} \\
&+ (S_{j1t}-S_{j2t})\frac{S_{1t-1}-S_{2t-1}}{2} + (S_{j3t}-S_{j4t})\frac{S_{3t-1}-S_{4t-1}}{2}
\end{aligned}
$$

Denote the average market share of segments composed of products 1 and 2, $\bar{S}_{1-2,t}$ and $\bar{S}_{3-4,t}$ for 3 and 4. Then, an approximation of market share $S_{jt}(S_{t-1};p_t)$ that uses information only on segment market shares is

$$
\tilde{S}(\bar{S}_{1-2,t-1},\bar{S}_{3-4,t-1};p_{1-2,t},p_{3-4,t}) = (S_{j1t}+S_{j2t})\frac{S_{1-2,t-1}}{2} + (S_{j3t}+S_{j4t})\frac{S_{3-4,t-1}}{2}
$$

The question is how good of an approximation this is. In principle, this is a bad approximation since brand loyalty makes the demand for repeated choices much bigger than for any other product. Then, the approximation error of the demand for good 1 is

$$
(S_{11t}-S_{12t})\frac{S_{1t-1}-S_{2t-1}}{2} + (S_{13t}-S_{14t})\frac{S_{3t-1}-S_{4t-1}}{2}
$$

If consumer preferences for products 3 and 4 are similar, then the second term is likely to be small because the demand for good 1 coming from good 3 or 4 should be relatively similar. However, the demand for good 1 coming from good 1 or two should be significantly different due to brand loyalty. However, the approximation for the market segment demand is much better. That is, the approximation error for market segments 1-2 is,

$$
[(S_{11t}-S_{22t})+(S_{21t}-S_{12t})]\frac{S_{1,t-1}-S_{2,t-2}}{2} + [(S_{13t}-S_{14t})+(S_{23t}-S_{24t})]\frac{S_{3,t-1}-S_{4,t-2}}{2}
$$

Now both terms should be close to zero, as if the demand for good 1 coming from good 1 and the demand for good 2 coming from good are approximately similar, which is especially true when switching costs are high. Therefore, our approach suggests that reducing the state space to market shares of segments whose components firm price uniformly and whose perceived characteristics are also similar should be close to "payoff relevant". Denoting segments by h, we can transition as,

$$
\tilde{S}_{1-2,t}(\{\tilde{S}_{h,t-1}\},\{p_{ht}\}) = \frac{(S_{11}+S_{12}+S_{21}+S_{22})}{2}\tilde{S}_{1-2,t-1} + \frac{(S_{13}+S_{14}+S_{23}+S_{24})}{2}\tilde{S}_{3-4,t-1}
$$

The terms $\frac{(S_{11}+S_{12}+S_{21}+S_{22})}{2}$ and $\frac{(S_{13}+S_{14}+S_{23}+S_{24})}{2}$ can be computed exactly from an estimated demand using every single product or can be computed implicitly at estimation by aggregating market segments at estimation time.

Moreover, market segment aggregation delivers a good approximation of static payoffs if costs across products within the segment are similar. To see this observe that,

$$\pi_{1-2,t}((\{S_{j,t-1}\},\{p_{ht}\},\{c_j\}_{1,2}) = M \times \tilde{S}_{1-2,t}(\{\tilde{S}_{h,t-1}\},\{p_{ht}\})(p_{1-2,t} - \frac{c_1+c_2}{2}) + (\frac{c_1-c_2}{2})(S_{1t} - S_{2t})$$

Hence, the static profit error of approximation is,

$$\pi_{1-2,t}((\{S_{j,t-1}\},\{p_{ht}\},\{c_j\}_{1,2}) - \tilde{\pi}_{1-2,t}((\{\tilde{S}_{h,t-1}\},\{p_{ht}\},c_{1-2}) = (\frac{c_1-c_2}{2})(S_{1t} - S_{2t})$$

and the implicit cost primitives to recover are the average marginal costs of products within the segment.

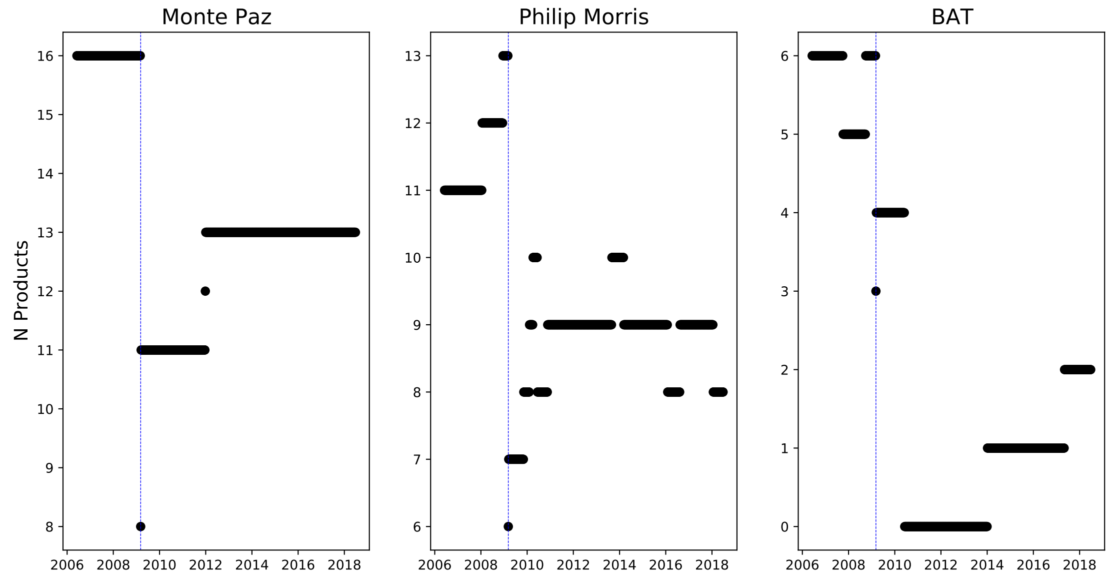
To sum up, leaving entry/exit considerations aside, we could aggregate products within a segment without losing much information on transitions (demand) and static payoffs (profits) if 1) consumers value products similarly, 2) they are priced uniformly, and 3) the costs of production are homogeneous.

B.2.4 Product Entry & Exit

We have omitted product entry and exit so far. However, it is evident that to reduce the number of products, we need all products within a segment to be introduced and retired at the same time. Next, we describe the entry and exit patterns of products within a segment.

Monte Paz had a presence in four segments before the one-presentation-per-brand policy: flagship, light, other regular, and special products. After the policy, all light and special products were eliminated. They reintroduced the light products right away and waited two years to re-introduce the special products. They reintroduced these segments by launching one fewer product in each category (so, in each category, one product was not "substituted"). Hence, while Monte Paz product portfolio did not reach the exact same size as before, its shares within each segment were similar (see Figure B.4). Philip Morris suffered a large shock as a consequence of the policy. They lost all their light and retired other regular products shortly after. While they re-introduced an almost identical portfolio of light products after 10 months, they never reintroduced the other regular products. BAT did not face a significant shock as a consequence of the policy since its light segment was small. Indeed, after the policy, it reintroduced one product to recompose its light segment. However, in 2010 it took all its products off the market and re-entered in 2014 with just its premium products (two products) in 2014.

Figure B.4: Evolution of firms' product portfolio.



B.2.5 Considered Segments

Therefore, we use a four-level criterion to define each segment: similar consumer preferences, priced uniformly, being introduced or retired together within a short time, and similar marginal costs. The natural partition following these criteria would be to have eight product segments by firm. However, we simplify the problem in the following way. We only consider segments that had been observed sometime in our sample. This implies, for instance, that Monte Paz cannot have premium products or that Philip Morris and BAT do not have special products. Then, we assume that BAT segments only differentiate between the premium and standard dimensions since the light products within each vertical dimension represent a negligible share. On the other hand, for Philip Morris, we do not consider the premium-standard differentiation because they price them similarly, just setting a price gap between them that is constant throughout time. Moreover, Philip Morris introduced premium and non-premium products in the light segment simultaneously, following the one-presentation-per-brand. Thus, we define nine segments (4 Monte Paz, 3 Philip Morris, 2 BAT). Table **??** shows summary statistics by segment.

Segment	Number of Products	Average Price	Shares	Time in Sample
Monte Paz Leader	2.0	2.3	0.595	1.0
Monte Paz Other Regular	4.0	2.15	0.022	1.0
Monte Paz Light	4.5	2.3	0.086	1.0
Monte Paz Special	3.5	2.21	0.001	0.69
Philip Morris Leader	4.0	2.24	0.233	1.0
Philip Morris Light	3.5	2.25	0.049	0.94
Philip Morris Other Regular	4.0	1.9	0.006	0.17
BAT Leader	1.0	1.92	0.049	0.29
BAT Premium	3.5	2.08	0.004	0.63

B.3 State Dependence Reduced Form Test

Here we apply Shcherbakov [2016]'s reduced form strategy to get a first sense of which force dominates. We use our aggregate data source and regress current shares on lagged shares of the same product, average shares of all other products in the choice set, and prices.

$$s_{ijt} = \alpha_{0pjt} + \beta_0 s_{ij,t-1} + \beta_1 s_{i,(-j),t-1} + \gamma_t + \gamma_j + \varepsilon_{ijt}$$

Table B.3: Structural State Dependence versus Spurious Dependence

	(1) OLS	(2) IV
own lagged share	0.886***	0.676***
	(0.003)	(0.034)
lagged mean shares others	0.010***	-0.348***
	(0.003)	(0.069)
real price per cig	-0.011***	-0.015***
	(0.001)	(0.001)
N	188927	188927
R^2	0.929	0.892
Prod, Time FE	Yes	Yes
IVs	None	Lagged Prices

Although the OLS estimate of β_0 determines the correlation between current and lagged choices, yesterday's decisions are influenced by factors that are permanent throughout time but not observed by the econometrician. These unobserved factors make lagged choices endogenous to the error term. We use exogenous shifters of lagged choices as instruments to isolate the effect of past decisions on current ones from persistent factors.[39] Table B.3 shows the results, indicating that state dependence is a relevant force in our setting.

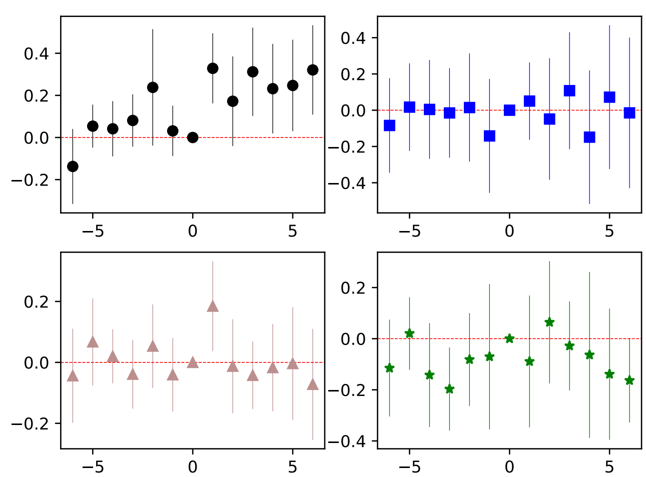
B.4 Product Substitution: An Event Study.

The one-presentation-per-brand (OPPB) policy trimmed the choice set and forced some consumers to make active choices. The choices between the remaining products help us isolate their preferences absent any state dependence. We illustrate this variation through an event study. Take any segment that goes out of the market due to the OPPB. Then, a store is considered to be treated following these products' exit if it used to offer those cigarettes in the past. Because not all stores sold all products, nor did they exit stores simultaneously, we characterize substitution patterns using the following regression framework:

$$\underbrace{s_{ijt}}_{\text{share product } j \text{ at store } i} = \tau_i + \delta_t + \sum_k \rho_{kj} \times 1\{\text{store } i \text{ sold product } k \cap \text{after } k \text{ exits}\} + \varepsilon_{ijt} \tag{29}$$

Figure B.5 presents the event study results for Philip Morris' light segment. We plot the $\rho_{j\text{PM, lights}}$ coefficients for the main remaining products: Monte Paz Flagship (black), Monte Paz Light (blue), Philip Morris Flagship (pink), BAT (green). Consumers appear to substitute proportionally to the product's aggregate shares as in a logit model. These results suggest little persistence of preferences: if consumers especially liked their products' characteristics, we would expect them to switch more to other light products (Monte Paz Lights) or other premium products (Philip Morris or BAT).

Figure B.5: Substitution following Philip Morris exit, an event study.

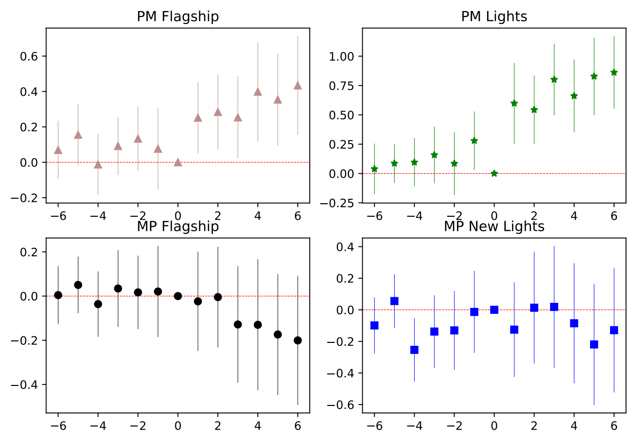


Furthermore, it is usually difficult to discern between consumers who are not price-sensitive and those who face high state dependence. Ideally, we want to observe active consumers making choices under various relative price scenarios to identify price sensitivity separately. We also find this type of variation in our

[39]Recall cigarette prices are uniform across stores. Hence, prices are exogenous to store-time specific shocks.

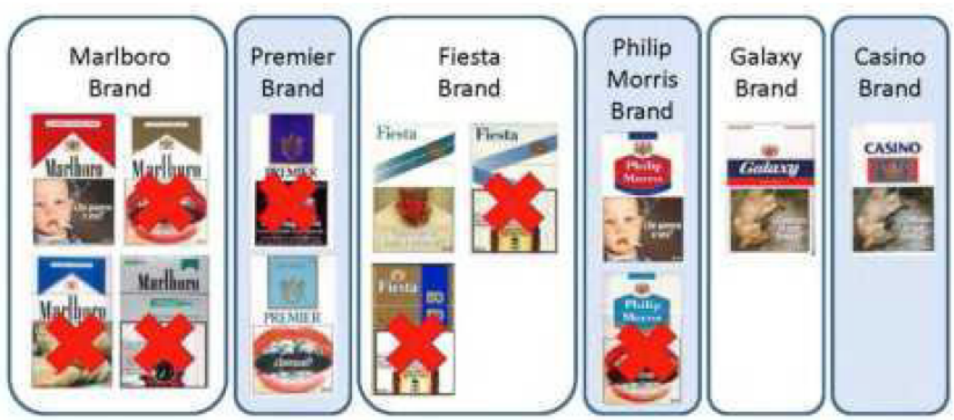
setting. At the time when the OPPB forced several products out of the market, relative prices between the firms were quite similar. However, when BAT exited the market, relative prices between Philip Morris were about 45% below the national firm. Figure B.6 shows that former BAT consumers switched predominantly to Philip Morris following the product exit. Hence, differences between the Philip Morris-BAT substitution between the two events directly inform consumers' price sensitivity, independent of any state dependence.

Figure B.6: Substitution following Monte Paz light exit, an event study.



B.5 Other Figures

Figure B.7: Philip Morris' portfolio and products affected by OPPB



B.6 Other Tables

Table B.4: Transition probabilities

lagged_product_id	product_id / wave	choice_prop bat_flagship	mp_flagship	mp_light	mp_regular	outside	pm_flagship	pm_light	pm_specials
bat_flagship	2	0.590909	0.227273	–	–	0.045455	0.136364	–	–
	3	–	0.150000	0.050000	0.100000	0.200000	0.300000	0.200000	–
	5	0.500000	–	–	–	0.500000	–	–	–
mp_flagship	2	0.007605	0.733840	0.049430	0.003802	0.190114	0.015209	–	–
	3	–	0.695652	0.038647	0.002415	0.212560	0.043478	0.007246	–
	4	–	0.722359	0.044226	0.007371	0.191646	0.029484	0.004914	–
	5	–	0.813433	0.027363	0.002488	0.141791	0.012438	0.002488	–
mp_light	2	–	0.378378	0.486486	–	0.081081	0.027027	0.027027	–
	3	–	0.347222	0.319444	0.041667	0.194444	0.083333	0.013889	–
	4	0.020408	0.244898	0.510204	–	0.204082	0.020408	–	–
	5	–	0.148936	0.680851	–	0.148936	0.021277	–	–
mp_regular	2	0.230769	0.153846	–	0.384615	0.230769	–	–	–
	3	–	0.055556	–	0.500000	0.333333	0.111111	–	–
	4	–	0.058824	–	0.470588	0.235294	0.058824	0.176471	–
	5	–	0.187500	0.187500	0.437500	0.187500	–	–	–
outside	3	–	0.153153	–	–	0.819820	0.027027	–	–
	4	0.004525	0.140271	0.009050	0.004525	0.773756	0.049774	0.018100	–
	5	–	0.203704	0.011111	0.003704	0.755556	0.025926	–	–
pm_flagship	2	–	0.063830	0.042553	–	0.234043	0.659574	–	–
	3	–	0.028169	–	–	0.281690	0.661972	0.028169	–
	4	0.008621	0.068966	0.008621	–	0.163793	0.750000	–	–
	5	–	0.145299	0.034188	–	0.085470	0.726496	0.008547	–
pm_light	2	0.125000	0.125000	–	–	–	–	0.625000	0.125
	3	–	–	–	0.062500	0.375000	0.500000	0.062500	–
	4	0.052632	0.315789	–	–	0.315789	0.105263	0.210526	–
	5	–	0.210526	–	–	0.105263	0.105263	0.578947	–
pm_specials	2	–	–	–	–	0.500000	0.500000	–	–
	3	–	0.500000	–	0.250000	0.250000	–	–	–

		choice_prop							
	product_id	bat_flagship	mp_flagship	mp_light	mp_regular	outside	pm_flagship	pm_light	pm_specials
lagged_product_id	wave								
bat_flagship	2	0.590909	0.227273	–	–	0.045455	0.136364	–	–
	3	–	0.150000	0.050000	0.100000	0.200000	0.300000	0.200000	–
	5	0.500000	–	–	–	0.500000	–	–	–
mp_flagship	2	0.007605	0.733840	0.049430	0.003802	0.190114	0.015209	–	–
	3	–	0.695652	0.038647	0.002415	0.212560	0.043478	0.007246	–
	4	–	0.722359	0.044226	0.007371	0.191646	0.029484	0.004914	–
	5	–	0.813433	0.027363	0.002488	0.141791	0.012438	0.002488	–
mp_light	2	–	0.378378	0.486486	–	0.081081	0.027027	0.027027	–
	3	–	0.347222	0.319444	0.041667	0.194444	0.083333	0.013889	–
	4	0.020408	0.244898	0.510204	–	0.204082	0.020408	–	–
	5	–	0.148936	0.680851	–	0.148936	0.021277	–	–
mp_regular	2	0.230769	0.153846	–	0.384615	0.230769	–	–	–
	3	–	0.055556	–	0.500000	0.333333	0.111111	–	–
	4	–	0.058824	–	0.470588	0.235294	0.058824	0.176471	–
	5	–	0.187500	0.187500	0.437500	0.187500	–	–	–
outside	3	–	0.153153	–	–	0.819820	0.027027	–	–
	4	0.004525	0.140271	0.009050	0.004525	0.773756	0.049774	0.018100	–
	5	–	0.203704	0.011111	0.003704	0.755556	0.025926	–	–
pm_flagship	2	–	0.063830	0.042553	–	0.234043	0.659574	–	–
	3	–	0.028169	–	–	0.281690	0.661972	0.028169	–
	4	0.008621	0.068966	0.008621	–	0.163793	0.750000	–	–
	5	–	0.145299	0.034188	–	0.085470	0.726496	0.008547	–
pm_light	2	0.125000	0.125000	–	–	–	–	0.625000	0.125
	3	–	–	–	0.062500	0.375000	0.500000	0.062500	–
	4	0.052632	0.315789	–	–	0.315789	0.105263	0.210526	–
	5	–	0.210526	–	–	0.105263	0.105263	0.578947	–
pm_specials	2	–	–	–	–	0.500000	0.500000	–	–
	3	–	0.500000	–	0.250000	0.250000	–	–	–

C Appendix: Computational Implementation

C.1 Equilibrium Computation Algorithm

We compute the equilibrium iterating in approximate best responses. We approximate the value function using Chebyshev Polynomials over Chebyshev nodes and solve for a fixed point in the space of the polynomials coefficients. In each step, we perform three tasks. First, we compute the best participation and price response given the trial value function approximation, rivals policies and firms beliefs. Then, we update firms beliefs according to new policies. Finally, we update values at the selected nodes and update the approximation, i.e., the polynomial coefficients.

C.1.1 Approximation

There are three type of states. The choice sets, which are discrete. The exogenous variables: preferences and costs. And the customer base (lagged market shares), which is continuous. Allowing for exogenous states (c_t, δ_t) is simple. We assume each of the exogenous states (c_t, δ_t) follow an independent AR(1) process, and discretize them using Tauchen's method. We call the resulting nodes $e \in \mathscr{E}$ and the transition matrix Π^e. On the other hand, the vector of own customer bases (S^f_{t-1}) and the tracked market moments $(\bar{S}^f_{t-1})$ aggregate is firm specific. We denote the whole vector z^f. To avoid solving the game for a large grid of possible values of z^f, we approximate the value function with a basis approximation such that for each possible choice set $\gimel$ and exogenous state e and firm f, we have

$$V_f(x, \gimel, e; q) = \sum_{n=0}^{N} q_n^{f,\gimel,e} T_n(x) \tag{30}$$

where each T_n is a Chebyshev basis of order n, and $\{q_n^{f,\gimel,e}\}_{n\in\{1,\ldots,N\}}$ are coefficients to be computed. Thus, we do not compute the fixed point of the value function but a fixed point of the coefficients $\{q_n^{f,\gimel,e}\}_{n\in\{1,..,N\},\gimel\in\mathscr{J}}$, for each possible choice set.

At each iteration k, we solve for $\{q_n^{f,\gimel,e}\}$. To solve for these coefficients, we must pick a set of nodes $\{z_i^f(\gimel, e) \in \mathscr{S}^{f,\gimel,e}\}$ for each firm f, choice set $\gimel$ and exogenous state e, where to solve the value function –and corresponding policies.[40] Choosing the nodes $\mathscr{S}^{f,\gimel,e}$ appropriately is key to getting sound convergence properties of the approximation [Judd, 1998, De Boor and De Boor, 1978]. We pick Chebyshev nodes over each dimension and solve the problem at the intersection of every dimension.[41] Note that we still face a curse of dimensionality on the dimension of each firm portfolio–not on the number of firms. We have solved the problem with up to five products per firm.

After evaluating the values at each node, $V_f(z_i^f(\gimel, e), \gimel, e)$, –see below– we find the optimal coefficients by OLS. That is we minimize the sum of the square distance of $\varepsilon_i^{f,\gimel,e} = V_f(z_i^f(\gimel, e), \gimel, e) - V_f(z_i^f(\gimel, e), \gimel, e; q)$,

[40] The i subscript indicate that it refers to particular nodes instead of the continuous vector z^f

[41] There is an additional complexity in our setting: the state space is not represented by "rectangles" since shares live in the simplex. We explore different solutions to this issue. In our main specification we add more nodes into each horizontal dimension and drop the nodes that lie outside the simplex. In a robustness check, we use a transformation of the state space that allows us to project points from rectangles to the simplex and vice versa. We find the former to work better in our case.

that is

$$\hat{q}_n^{f,\gimel,e} = \arg\min_{q\in\mathbb{R}^N} \sum_i (\varepsilon_i^{f,\gimel,e})^2$$

Finally, observe that taking derivatives of the value function (or any approximation) can be performed efficiently since it amounts to taking derivatives of a polynomial.

C.1.2 Updating Firms Beliefs

We enter each step k of the iteration holding $\hat{q}_{k-1}^{f,\gimel,e}$, $\sigma_{k-1}^{p}, \sigma_{k-1}^{\phi}$ in memory. Here, σ^p, σ^ϕ refers also to prices and probabilities of participation for each product j at each node $z_i^f(\gimel, e)$ for each choice set $\gimel$ and exogenous state e, evaluated by each firm f.[42]

In the first step we solve for iteration k optimal prices σ_k^p, holding values and rivals policies constant. In order to solve these policies, we need to compute firm f expected profits and transitions for every possible vector of price p'_f, firm f might set.

Appendix A.1 describes how firms form beliefs about payoff relevant states from information sets I_f, i.e from $(z_i^f, \gimel, e)$. Here, it suffices to say that for each realization of the information set I_f firms can compute rivals customer base $S_{-f,t-1}^f$, which also allow them for construct rivals information sets I_{-f}^f.[43] Then, firms can evaluate rivals' actual policies $\sigma_{k,-f}$ at I_{-f}^f to assess rivals expected actions. Naturally, I_{-f}^f is not an element of $(z_i^{-f}, \gimel, e)$. Hence, we need to interpolate the policy function of rivals $-f$ to evaluate it at I_{-f}^f. We do this using the same Chebyshev basis approximation as in the value function.

This information is enough to compute expected profits and transitions, because are both determined by the demand for each product j at each node $z_i^f(\gimel, e)$. Integrating over the conditional distribution of types $w[n|k]$, conditional on lagged consumption, and firms assessment customer bases $S_{s,t-1}^f$ for each product s and rivals prices $\sigma_{-f}^p(I_{-f}^f)$ we get

$$S_{jt}^f(z_i^f(\gimel, e), \gimel, e; \sigma) = \sum_{s=1}^{F} \sum_{n=1}^{N} S_{snjt}(p_{ft}, \mathbb{J}, e; \sigma_{-f}(I_{-f}^f); \mu^D) \times S_{s,t-1}^f \times w[n|k] \tag{31}$$

C.1.3 Policy Step

Participation Policy Step Due to our timing assumption, participation decisions are made at the end of the period, once new market shares realize. Optimal prices at iteration k determine σ_k^p. Hence, firms' perceived vector of demand is $S_t^f(z_i^f(\gimel, e), \gimel, e; \sigma_k^p)$, following Equation 31. Then, participation best responses are determined by evaluating the right-hand side of Equation 9, using $V_f(x, \gimel, e; \hat{q}_k)$ evaluated at $x = S_{jt}^f(z_i^f(\gimel, e), \gimel, e; \sigma_k^p)$. At this point, we can either update firms' best responses or perform several iterations of the fixed point problem to get a better approximation of optimal participation probabilities at the current value function approximations.

[42] Note that the product j defines the firm f

[43] The suprascripts reflect the agent forming beliefs.

Price Policy Step At the beginning of the period firms optimize over prices. Thus, to compute price's best responses, we must calculate values and participation derivatives at the demand generated by each trial price p_j at every possible node $z_i^f(\daleth, e)$ for each choice set and exogenous states, holding rivals' strategies fixed: $S_t^f(z_i^f(\daleth, e), \daleth, e; \sigma^p_{k-1,-f}, p_j)$.

$S_t^f(z_i^f(\daleth, e), \daleth, e; \sigma^p_{k-1,-f}, p_j)$ is immediate to compute from our information hold in memory. Evaluating values and participation derivatives is also straightforward. To evaluate the derivates of the value function, we can take derivatives of the approximated polynomials from the previous step, $V_f(x, \daleth, e; \hat{q}_{k-1})$ and evaluate it at $S_t^f(z_i^f(\daleth, e), \daleth, e; \sigma^p_{k-1,-f}, p_j)$. In the case of participation derivatives, we can use the fact that the participation threshold is a function of the value function and the distribution of fixed costs. Indeed, under a distributional assumption (exponentially distributed fixed costs) we can compute the derivative of participation policies in closed form using the implicit function theorem —see Appendix A.4.1.

Hence, evaluating the right-hand side of Equation 13 is not computationally demanding. By doing so, we can compute the next guess of prices towards its fixed point. Finally, we might speed up computations by not solving the fixed point at every iteration k but only make decent progress toward it. Although we can reach the value function's fixed point faster by not forcing prices to be optimal on each step, we ensure that equilibrium prices are indeed optimal once we reach the fixed point of the value function operator.

C.1.4 Value function update

Finally, we update the values at each interpolating node z_i, choice set $\daleth$ and exogenous state e, $V_{k+1}(z_i, \daleth, e)$, using $\sigma^p_{kf}(z_i^f, \daleth, e)$, $\sigma^\phi_{kf}(S^f, \daleth, e')$, and $V_{fk}(S^f, \daleth', e', \hat{q}_k)$. While computing variable profits at optimal prices and expected continuation payoffs (from previously computed values) is immediate, obtaining the expected value of fixed costs conditional on participating is slightly more difficult. However, under our assumption that fixed costs are distributed exponentially with mean values θ_{FC} we can compute the next period's values in closed form as[44]

$$
\begin{aligned}
&V_{f,k+1}(z_i^f, \daleth, e) = M \times S^f_{jt}(z_i^f, \daleth, e; \sigma^p_k) \times (\sigma^p_{kj(f)}(z_i^f, \daleth, e) - c_{j(f)}(e)) - \\
&\sum_{e' \in \mathscr{E}} \Big(\phi_{kj(f)}(S_t^f(z_i^f, \daleth, e; \sigma^p_k), \daleth, e') \times \theta_{FC} - \Big[1 - \phi_{kj(f)}(S_t^f(z_i^f, \daleth, e; \sigma^p_k), \daleth, e')\Big] \times \bar{\Theta}(S_t^f(z_i^f, \daleth, e; \sigma^p_k), \daleth, e'; \phi_k) Pr(e'|e) \Big) + \\
&\sum_{e' \in \mathscr{E}} \sum_{\daleth' \in \mathscr{J}} V_{f,k}(S_t^f(z_i^f, \daleth, e; \sigma^p_k), \daleth', e'; \hat{q}_k) Pr(\daleth'|\phi_k) Pr(e'|e))
\end{aligned}
\tag{32}
$$

Then, we proceed to the next iteration. Let Ψ^p and Ψ^ϕ refer to the RHS of Equation 13 and Equation 9 respectively, and denote Equation 32 the Bellman Equation. Algorithm 1 describes the algorithm used to solve for the equilibrium.

[44] We are omitting the explicit dependence of z_i^f on $\daleth$ and e to avoid loading the notation.

Algorithm 1 Equilibrium Solver

Choose projection nodes $\mathscr{S} \to$ state space is $\mathscr{X} = \mathscr{S} \times \mathscr{J}$.
Set $V_f^0[x] \quad \forall x \in \mathscr{X}, f$

---

while $crit^V > tol^V$ **do**
  while $crit^\phi > tol^\phi$ or iter$^\phi <$ maxiter(k_ϕ) **do**
    $Pr(\beth'|\beth) \leftarrow \sigma^\phi_{k_\phi - 1}$
    $\sigma^\phi_{k_\phi} \leftarrow \Psi^\phi \left(V_f(S_t^f(\sigma^p_{k-1}); \hat{q}_{k-1}), S_t^f(\sigma^p_{k-1}), Pr(\beth'|\beth) \right)$
    $crit^\phi = ||\sigma^\phi_{k_\phi+1(k_p)} - \sigma^\phi_{k_\phi(k_p)}||/||\sigma^\phi_{k_\phi(k_p)}||$
  end while

  Set $\sigma_f^{p,0(k_V)}$
  while $crit^p > tol^p$ or iter$^p <$ maxiter(k_p) **do**
    $\nabla_S V_f(S^f_{k_p-1}(\sigma^p_{k_p-1}); \hat{q}_{k-1}) \leftarrow$ derivative of Chebyshev polynomials
    $\nabla_S \sigma_k^\phi at S^f_{k_p-1}(\sigma^p_{k_p-1}) \leftarrow$ by IFT
    $\sigma^p_{k_p} \leftarrow \Psi^p \left(S^f_{k_p-1}, \nabla_S V_f, \nabla_S \sigma_k^\phi, Pr(\beth'|\beth), Pr(e'|e) \right)$
    $S^f_{k_p} \leftarrow \sigma^p_{k_p}$ according to Equation 31
    $crit^p = ||\sigma^p_{k+1(k_V)} - \sigma^p_{k(k_V)}||/||\sigma^p_{k(k_V)}||$
  end while

  Update $V_f^k \leftarrow$ according to Equation 32
  Compute $\{\hat{q}_k\}$ by OLS.
  $crit^V = ||V_k - V_{k-1}||/||V_{k-1}||$
end while

C.2 Absorbing Steady State in Dynamic Game without Entry and Exit

We have mentioned that we select the MPE by initializing the algorithm at the absorbing steady state. In this section, we describe how we compute the absorbing steady state.

Algorithm 2 Equilibrium at absorbing state for fixed choice sets — based on MacKay and Remer [2021].

1: Initialize price policy's derivative: $\nabla_s \sigma_0^p$.
2: **while** $crit > tol$ **do**
3: At each iteration k, initialize $\sigma_0^p(k)$
4: **while** $crit^p > tol^p$ **do**
5: $S^{ss}(p_{k_P(k)}) \leftarrow S = S(p_{k_P(k)}, S)$.
6: $\nabla_S V_f(S^{ss}(p_{k_P(k)})) \leftarrow \nabla_S V_f = \nabla_S \pi_f + \nabla_p \pi_f \nabla_S \sigma_k^p + \nabla_S V_f^T \left[\nabla_S S + \nabla_p S \nabla_S \sigma_k^p\right]$
7: $p^{k_p+1(k)} \leftarrow$

$$p_f^{k_p+1(k)} = \left(c_f - \frac{\beta}{M}\frac{\partial V_f}{\partial S_f}\right) - \frac{S_f}{\frac{\partial S_{ft}}{\partial p_f}} - \sum_{r:\mathbf{J}_r=1, k\neq f} \frac{\frac{\partial S_k}{\partial p_f}}{\frac{\partial S_f}{\partial p_f}} \left(\frac{\beta}{M}\frac{\partial V_f}{\partial S_r}\right)$$

8: $crit^p = ||p^{k+p+1(k)} - p^{k_p(k)}||/||p^{k_p(k)}||$
9: **end while**
10: $\frac{\partial \sigma_{k+1}^p}{\partial S} \leftarrow$ numerically differentiating p_k^*.
11: $crit = ||\nabla_S \sigma_{k+1}^p - \nabla_S \sigma_k^p||/||\nabla_S \sigma_k^p||$
12: **end while**

The crucial aspect of the computation is that we can leverage restrictions about the absorbing steady-state. In particular, we solve for the steady state shares for any guess of prices from $S^{ss}(\gimel) = S(S^{ss}, \gimel, P)$. Additionally, we can solve for the value function derivatives (at any market share) given a guess of the price policy derivatives. Therefore, we solve for steady state prices from a guess of price policy derivatives, iterating on firms' FOC. Finally, we can update our price policies' derivatives guess, by numerically differentiating these prices. Algorithm 2 describes the algorithm for any of these choice sets.

Therefore, we can circumvent the curse of dimensionality that would otherwise arise from solving for the equilibrium at each point in the state space. Hence, we can quickly obtain the value at such a point. The following algorithm details our computations. We solve the steady state for every choice set $\gimel$, assuming it will remain constant in the future.

C.3 Multi-Product Price Inversion

Once we move into the multi-product case, we carry out price updates (line 14 in Algorithm 1 and line 7 in Algorithm 2) using Morrow and Skerlos [2011] as described in Conlon and Gortmaker [2020]. It requires minimal changes to adapt Morrow and Skerlos [2011] inversion to the dynamic setting used in this paper. Recall, that the derivative of market shares with respect to prices can be broken up into two parts

$$\frac{\partial S}{\partial p}(p) = \Lambda(p) - \Gamma(p)$$

where Λ is a diagonal matrix with diagonal elements

$$\Lambda_{jj} = \sum_w \sum_n (-\alpha_n) S_j(w,n) dF(D_n|w) dF(w)$$

and Γ is a dense matrix with elements

$$\Gamma_{jk} = \sum_w \sum_n \alpha_n S_j(w,n) S_k(w,n) \frac{\partial S_k(w)}{\partial p_j} dF(D_n|w) dF(w)$$

with $dF(D_n|w)$ and $dF(w)$ denoting the weights of consumer types conditional on consuming product w in the past and $dF(w)$ indicates the share of product w consumers.

Then, price FOC can be written as

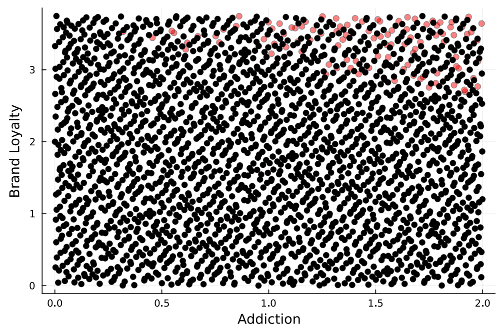
$$p = c + \Lambda(p)^{-1}(\mathscr{O}.\times\Gamma(p))(p-c) - \Lambda^{-1}(p)\left\{S + \frac{\beta}{M}\times\nabla_p S\times E[\nabla_S V] + \frac{\beta}{M}\nabla_p S\times\sum_{-f}\left(E[V|\mathbf{J}_{-f}=1] - E[V|\mathbf{J}_{-f}=0]\right)\nabla_S\phi_{-f}\right\}$$

D Appendix: Convergence and Multiplicity

D.1 Convergence & Existence

As we commented in Section 2, there are no guarantees that an equilibrium exists or is unique. However, our algorithm converges for wide regions of the parameter space, which we take as strong evidence that existence is not a significant issue–see Figure 1. We observe some non-convergence at high inertia values, but we believe these are more closely related to issues with the parametric approximations when the model becomes highly non-linear than evidence of non-existence.

Figure 1: Convergence Plots



D.2 Multiplicity in game without entry and exit

We then explore equilibrium multiplicity in the game without entry and exit, using several techniques. First, we use our simulation design. We draw 5000 simulated primitives with replacement and solve the game without entry and exit for each draw. We then regress equilibrium outcomes on primitives and find that they explain more than 99% of the equilibrium outcomes variation. Table 1 shows the results of the regressions on shares, and Table 2 on prices.

Table 1: Regression of equilibrium shares of the game without entry and exit, on primitives

	Share Leader (new draw)	Share Leader (original)	Share Follower (new draw)	Share Follower (original)
	(1)	(2)	(3)	(4)
(Intercept)	-0.189***	-0.189***	-0.225***	-0.225***
	(0.002)	(0.002)	(0.002)	(0.002)
addiction	0.089***	0.089***	0.069***	0.069***
	(0.000)	(0.000)	(0.000)	(0.000)
addiction sq	-0.002***	-0.002***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
brand loyalty	0.126***	0.126***	0.065***	0.065***
	(0.001)	(0.001)	(0.001)	(0.001)
brand loayalty sq	-0.009***	-0.009***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
compensated utility	0.184***	0.184***	0.163***	0.163***
	(0.001)	(0.001)	(0.001)	(0.001)
compensated utility sq	-0.011***	-0.011***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
addiction x brand loyalty	-0.011***	-0.011***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
brand loyalty x utility	-0.009***	-0.009***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Estimator	OLS	OLS	OLS	OLS
N	4,997	4,997	4,997	4,997
R^2	0.996	0.996	0.995	0.995

Note:

Table 2: Regression of equilibrium prices of the game without entry and exit, on primitives

	Price Leader (new draw)	Price Leader (original)	Price Follower (new draw)	Price Follower (original)
	(1)	(2)	(3)	(4)
(Intercept)	1.736***	1.736***	1.918***	1.918***
	(0.006)	(0.006)	(0.006)	(0.006)
addiction	0.014***	0.014***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
addiction sq	0.014***	0.014***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
brand loyalty	-0.139***	-0.139***	-0.206***	-0.206***
	(0.002)	(0.002)	(0.002)	(0.002)
brand loayalty sq	0.043***	0.043***	0.046***	0.046***
	(0.000)	(0.000)	(0.000)	(0.000)
compensated utility	0.293***	0.293***	0.194***	0.194***
	(0.004)	(0.004)	(0.004)	(0.004)
compensated utility sq	-0.022***	-0.022***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
addiction x brand loyalty	0.045***	0.045***	0.042***	0.042***
	(0.000)	(0.000)	(0.000)	(0.000)
brand loyalty x utility	0.015***	0.015***	0.018***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Estimator	OLS	OLS	OLS	OLS
N	4,997	4,997	4,997	4,997
R^2	0.992	0.992	0.990	0.990

Note:

We complement this analysis with more formal methods to look for multiplicity robustly. First, we use the method suggested by Reguant and Pareschi [2021] to bound all feasible counterfactual outcomes in a simplified version of the game.[45] The equilibrium bounds are narrow for large regions of the parameter

[45]The simplified version is equivalent to the model in Dubé et al. [2009] and Chen [2016]. The main difference to our baseline

space, indicating that the equilibrium is likely to be unique. Moreover, we employ homotopy to find all equilibria of the game as in Besanko et al. [2010]. Again, we find no evidence of multiplicity.[46]

D.3 Equilibrium Selection

Then, we use the solution of the steady state of the game without entry and exit as the initial values to start the algorithm that solves the full game. Although this method does not guarantee that the selected equilibrium is the same for every parameter, we find evidence supporting it. Concretely, we regress equilibrium outcomes on primitives. Table 3, Table 4, and Table 5 show the results of the regressions. We find that the primitives almost perfectly explain the equilibrium outcomes after we follow such equilibrium selection.

Table 3: Regression of Equilibrium Participation on Primitives

	Participation Leader		Participation Follower	
	(1)	(2)	(3)	(4)
(Intercept)	-2.332***	-3.459***	0.176*	-10.562**
	(0.068)	(0.876)	(0.079)	(3.246)
addiction	0.750***	1.027***	-0.165***	2.236**
	(0.022)	(0.227)	(0.025)	(0.843)
addiction sq	-0.042***	-0.055**	0.030***	-0.086
	(0.002)	(0.017)	(0.002)	(0.064)
brand loyalty	0.772***	1.209***	-0.100***	4.812***
	(0.017)	(0.332)	(0.020)	(1.229)
brand loayalty sq	-0.046***	-0.081*	0.006***	-0.547***
	(0.001)	(0.033)	(0.001)	(0.123)
utility	1.506***	1.936***	0.069	0.646
	(0.038)	(0.282)	(0.045)	(1.045)
utility sq	-0.182***	-0.187***	0.014*	0.108
	(0.005)	(0.028)	(0.006)	(0.103)
addiction x brand loyalty	-0.089***	-0.149***	0.026***	-0.537***
	(0.003)	(0.040)	(0.003)	(0.147)
addiction x utility	-0.166***	-0.218***	0.067***	0.032
	(0.006)	(0.039)	(0.007)	(0.145)
brand loyalty x utility	-0.165***	-0.276***	0.031***	-0.161
	(0.005)	(0.048)	(0.006)	(0.178)
Estimator	OLS	OLS	OLS	OLS
N	2,241	154	2,241	154
R^2	0.978	0.957	0.987	0.889

This is evidence that our procedure effectively selects the same equilibrium every time, even though multiple equilibria might exist. The only region where the explanatory power of primitives is relatively low is for prices at high inertia levels (when the average probability of repeating product choices is above 85%).

model is that firms face a single consumer whose affiliation evolves over time. Under that specification, the equilibrium of the game exits, and computations simplify.

[46] pending

Nevertheless, it is hard to disentangle the effect of multiplicity from deficient parametric approximations in highly non-linear regions of the parameter space. In any case, we flag that region as problematic.

Table 4: Regression of Equilibrium Prices on Primitives

	Price, No Entry/Exit, Leader	Price, MPE, Leader		Price, No Entry/Exit, Follower	Price, MPE, Follower	
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	1.989***	1.648***	0.250	2.208***	2.310***	-6.818
	(0.030)	(0.052)	(2.043)	(0.030)	(0.040)	(4.174)
addiction	-0.071***	-0.126***	0.546	-0.114***	-0.070***	0.704
	(0.009)	(0.016)	(0.530)	(0.010)	(0.013)	(1.084)
addiction sq	0.021***	0.041***	-0.033	0.019***	0.014***	0.077
	(0.001)	(0.002)	(0.040)	(0.001)	(0.001)	(0.082)
brand loyalty	-0.201***	-0.211***	0.409	-0.273***	-0.085***	5.353***
	(0.008)	(0.013)	(0.774)	(0.008)	(0.010)	(1.581)
brand loayalty sq	0.048***	0.058***	-0.017	0.051***	0.014***	-0.665***
	(0.001)	(0.001)	(0.078)	(0.001)	(0.001)	(0.159)
utility	0.152***	0.389***	0.365	0.031	-0.035	-1.526
	(0.017)	(0.029)	(0.658)	(0.017)	(0.023)	(1.344)
utility sq	-0.002	-0.036***	-0.077	0.006*	0.018***	0.502***
	(0.002)	(0.004)	(0.065)	(0.002)	(0.003)	(0.132)
addiction x brand loyalty	0.054***	0.089***	-0.039	0.052***	0.006***	-0.428*
	(0.001)	(0.002)	(0.093)	(0.001)	(0.002)	(0.189)
addiction x utility	0.024***	0.024***	-0.004	0.027***	0.019***	0.502**
	(0.003)	(0.005)	(0.091)	(0.003)	(0.004)	(0.187)
brand loyalty x utility	0.031***	0.026***	0.062	0.036***	-0.004	-0.098
	(0.002)	(0.004)	(0.112)	(0.002)	(0.003)	(0.229)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	2,241	2,087	154	2,241	2,087	154
R^2	0.992	0.985	0.908	0.991	0.991	0.485

Table 5: Regression of Equilibrium Shares on Primitives

	Share, No Entry/Exit, Leader	Share, MPE, Leader		Share, No Entry/Exit, Follower	Share, MPE, Follower	
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-0.432***	-1.284***	0.349	-0.233***	0.074***	-3.155***
	(0.009)	(0.054)	(1.382)	(0.009)	(0.017)	(0.726)
addiction	0.169***	0.306***	-0.371	0.071***	-0.071***	0.623**
	(0.003)	(0.017)	(0.359)	(0.003)	(0.005)	(0.188)
addiction sq	-0.008***	-0.012***	0.050	0.000	0.009***	-0.022
	(0.000)	(0.002)	(0.027)	(0.000)	(0.000)	(0.014)
brand loyalty	0.184***	0.224***	-0.214	0.063***	0.006	1.407***
	(0.002)	(0.014)	(0.523)	(0.002)	(0.004)	(0.275)
brand loayalty sq	-0.013***	0.001	0.036	-0.000	-0.003***	-0.157***
	(0.000)	(0.001)	(0.053)	(0.000)	(0.000)	(0.028)
utility	0.319***	0.697***	0.377	0.169***	-0.072***	0.248
	(0.005)	(0.030)	(0.445)	(0.005)	(0.009)	(0.234)
utility sq	-0.029***	-0.074***	0.050	-0.010***	0.027***	0.027
	(0.001)	(0.004)	(0.044)	(0.001)	(0.001)	(0.023)
addiction x brand loyalty	-0.021***	-0.009***	0.135*	-0.003***	0.002**	-0.147***
	(0.000)	(0.002)	(0.063)	(0.000)	(0.001)	(0.033)
addiction x utility	-0.023***	-0.053***	-0.076	-0.001	0.035***	-0.000
	(0.001)	(0.005)	(0.062)	(0.001)	(0.001)	(0.032)
brand loyalty x utility	-0.025***	-0.023***	-0.063	-0.003***	0.002	-0.064
	(0.001)	(0.004)	(0.076)	(0.001)	(0.001)	(0.040)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	2,241	2,087	154	2,241	2,087	154
R^2	0.998	0.987	0.884	0.997	0.996	0.863

E Demand Estimation - Methodological Details and Additional Results (in progress)

E.1 Model Fit and Robustness Checks

Table E.1: Predicted and Observed Switching

	Outside	MP Flag.	MP Light	MP Other	PM Flag.	PM Prem	PM Light	PM Light Prem	PM Other	BAT	BAT Prem
Outside	0.78, 0.78	0.17, 0.09	0.01, 0.03	0.0, 0.01	0.01, 0.04	0.02, 0.03	0.01, 0.01	0.01, 0.01	nan, nan	nan, nan	0.0, 0.01
MP Flag	0.18, 0.13	0.74, 0.79	0.04, 0.02	0.0, 0.01	0.01, 0.02	0.02, 0.02	0.0, 0.01	0.0, 0.01	nan, 0.0	0.01, 0.03	nan, 0.01
MP Light	0.16, 0.26	0.28, 0.11	0.5, 0.5	0.04, 0.02	0.03, 0.05	0.03, 0.03	0.03, 0.01	0.01, 0.01	nan, 0.01	nan, 0.06	0.02, 0.01
MP Other	0.25, 0.35	0.11, 0.16	0.19, 0.05	0.45, 0.3	0.06, 0.07	0.06, 0.04	0.18, 0.02	nan, 0.01	nan, 0.01	0.23, 0.07	nan, 0.02
PM Flag.	0.18, 0.23	0.07, 0.1	0.03, 0.03	nan, 0.02	0.69, 0.57	0.04, 0.03	nan, 0.01	0.02, 0.01	nan, 0.0	nan, 0.05	nan, 0.01
PM Prem	0.2, 0.27	0.11, 0.12	0.09, 0.04	nan, 0.02	0.04, 0.05	0.61, 0.48	nan, 0.01	0.04, 0.01	nan, 0.01	nan, 0.05	0.02, 0.01
PM Light	0.31, 0.42	0.23, 0.17	nan, 0.05	nan, 0.02	0.23, 0.07	nan, 0.05	0.36, 0.26	0.09, 0.01	0.2, 0.01	0.2, 0.08	0.11, 0.02
PM Light Prem	0.26, 0.41	0.26, 0.19	nan, 0.06	0.07, 0.02	0.21, 0.07	0.17, 0.06	0.1, 0.02	0.45, 0.15	nan, 0.01	nan, 0.08	nan, 0.02
PM Other	0.38, 0.48	0.5, 0.19	nan, 0.06	0.25, 0.03	0.5, 0.09	nan, 0.05	nan, 0.02	nan, 0.01	nan, 0.09	nan, 0.11	nan, 0.01
BAT	0.1, 0.39	0.2, 0.14	0.05, 0.04	0.11, 0.02	0.2, 0.06	0.05, 0.05	0.16, 0.02	0.05, 0.01	nan, 0.01	0.57, 0.59	nan, 0.01
BAT Prem	0.75, 0.4	nan, 0.18	nan, 0.06	nan, 0.03	nan, 0.07	nan, 0.07	nan, 0.02	nan, 0.02	nan, 0.01	nan, 0.08	0.75, 0.19

Note: Switching rates are both calculated at eight quarter periods, which represents the frequency at which we observe individuals.

F Appendix: Supply Estimation

F.1 Moment Selection and Empirical Objective Function

Let $q_1(\chi_{kt}, \mathbb{X}_{kt}, \theta) = \chi_{kt} - E[\sigma_k^{\chi}(\tilde{S}_{t-1}^f, \mathbb{J}_t, \delta_t, tax_t; \varepsilon_t, \Theta_{kt}; \theta_0)|\mathbb{X}_{kt}]$, $q_2(p_{kt}, \mathbb{X}_{kt}, \theta) = p_{kt} - E[\sigma^p(\tilde{S}_{t-1}, \mathbb{J}_t, \delta_t, tax_t; \varepsilon_t; \theta)|\mathbb{X}_{kt}]$, and $q(\chi_{kt}, p_{kt}, \mathbb{X}_{kt}; \theta)$ the vertical stack of q_1 and q_2. Then we can form unconditional moments for chosen basis of $\mathbb{X}_{kt}$ -or other suitable instruments, $h_1(\mathbb{X}_{kt})$ and $h_2(\mathbb{X}_{kt})$ as:

$$g(\chi_{kt}, p_{kt}, \mathbb{X}_{kt}; \theta) = E\begin{pmatrix} q_1(\chi_{kt}, \mathbb{X}_{kt}, \theta) \times h_1(\mathbb{X}_{kt}) \\ q_2(p_{kt}, \mathbb{X}_{kt}, \theta) \times h_2(\mathbb{X}_{kt}) \end{pmatrix} = 0 \quad at\, \theta = \theta_0$$

If the model is overidentified, then we can construct the objective function G such that θ_0 minimizes it,

$$G(\theta) = g(\mathbb{X}_{kt}; \theta)' W q(\mathbb{X}_{kt}; \theta)$$

where W is a positive definite weighting matrix.

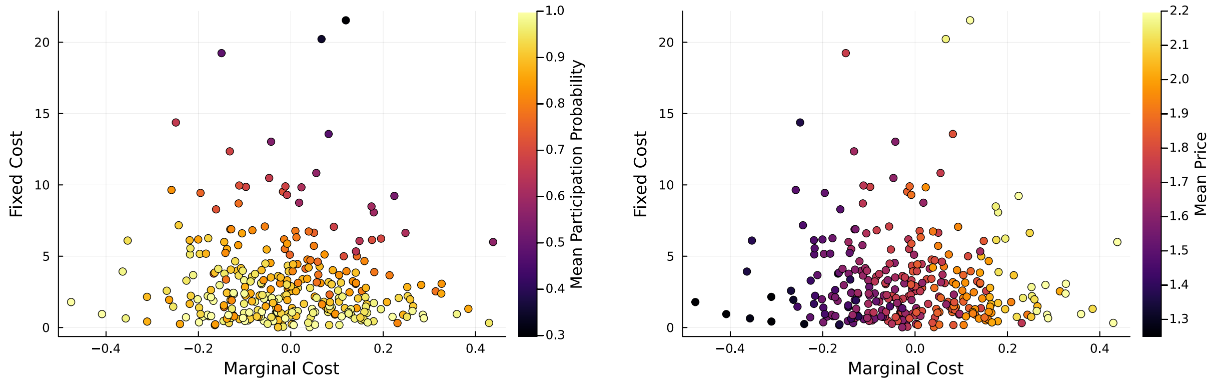
For each candidate parameter θ, we solve the equilibrium, compute the expected prices and participation functions, and construct the empirical version $G(\theta)$: $G_n(\theta)$. Our estimator is defined by

$$\hat{\theta} = \arg\min_{\theta} G_n(\theta)$$

Hansen [1982] establish the regularity conditions that ensure asymptotic normality of $\hat{\theta}$.

Identification — Plane cuts implied by data. In Section 4.2 we argue that conduct still help us identify marginal and fixed costs despite the fact that we cannot break up the problem and identify marginal costs from prices and conduct, and fixed costs from participation choices and conduct. Here, we provide a graphical representation that illustrate that prices and participation choices contain distinct information about the sequence of marginal and fixed costs that can rationalize it. In other words, the participation and price optimality equations do not appear to be colinear. Figure F.1 shows the sequence of marginal and fixed costs that generate alternative BAT's flagship average prices and participation rates. Each dot represents a simulated parameter. Their color indicates the average price (right panel) they would set in our sample and the average participation probability (left panel). Then, observed prices and participation select different cuts of the plane

Figure F.1: Identification of Fixed and Marginal costs, an illustration with BAT prices and participation rates.

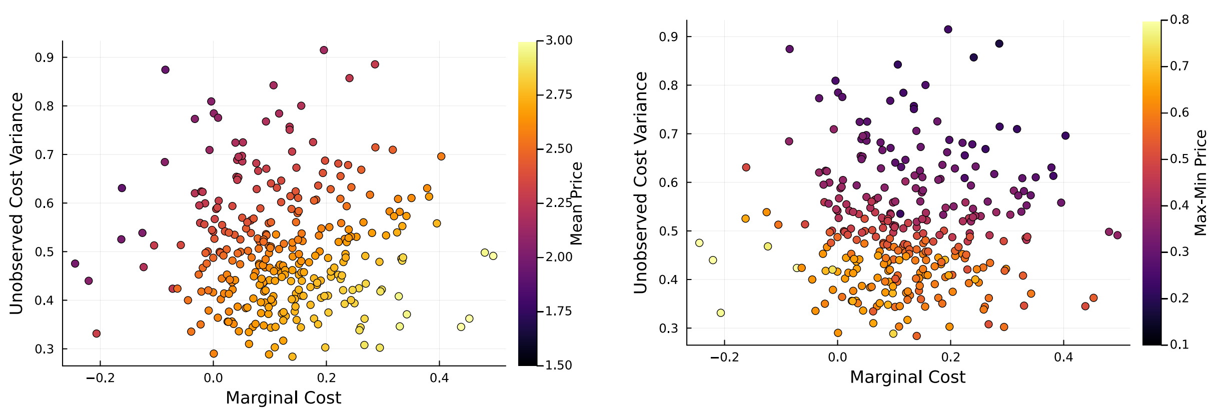


(a) Participation Rates

(b) Average Prices

We then observe that cost pass-through together with conduct also help ups identify the unobserved cost shocks. Figure F.2 illustrate how identification works. These plots show all possible mean prices (left panel) and price variation (the gap between the price at the max tax with respect to the min tax) that alternative pairs of marginal costs and unobserved cost variances could generate. Then, we use the observed mean prices and price variation to select the region of the marginal cost-unobserved cost variance plane that is compatible with the data.

Figure F.2: Identification of Unobserved Variance, an illustration with Monte Paz prices



(a) Average Prices

(b) Price gap between the maximum tax rate and minimum tax rate

Moment Selection Following the intuition in our previous arguments, we pick the basis (h_1, h_2) to match the average price and participation rates, their correlation with taxes, and their correlation with their customer bases. Then, we pick the corresponding basis h_1, h_2. h_1 are almost identical to h_2, and composed of dummy indicators for each product j, taxes, the products' own customer base, and other products' customer base. The first J moments are equivalent to match the average price and participation by product. The elements of h_2 are interacted by an indicator of whether these products are currently being offered in the market, because if they are not firms do not make price decisions. Hence, our empirical objective function is

$$
Gn(\theta) = \begin{pmatrix} \frac{1}{T}\sum_t q_{11t} \\ \vdots \\ \frac{1}{T}\sum_t q_{1Jt} \\ \frac{1}{T} q_{1jt} tax_t \\ \frac{1}{T} q_{1jt} S_{jt-1} \\ \frac{1}{T} q_{1jt} S^{\text{other}}_{jt-1} \\ \frac{1}{T_{\text{active}}} \sum_{t:\mathbb{J}_{1t}=1} q_{21t} \\ \vdots \\ \frac{1}{T_{\text{active}}} \sum_{t:\mathbb{J}_{tJ}=1} q_{2Jt} \\ \frac{1}{T_{\text{active}}} \sum_j \sum_{t:\mathbb{J}_{tJ}=1} q_{2jt} tax_t \\ \frac{1}{T_{\text{active}}} \sum_j \sum_{t:\mathbb{J}_{tJ}=1} q_{2jt} S_{jt-1} \\ \frac{1}{T_{\text{active}}} \sum_j \sum_{t:\mathbb{J}_{tJ}=1} q_{2jt} S^{\text{other}}_{jt-1} \end{pmatrix}' W \begin{pmatrix} \frac{1}{T}\sum_t q_{11t} \\ \vdots \\ \frac{1}{T}\sum_t q_{1Jt} \\ \frac{1}{T} q_{1jt} tax_t \\ \frac{1}{T} q_{1jt} S_{jt-1} \\ \frac{1}{T} q_{1jt} S^{\text{other}}_{jt-1} \\ \frac{1}{T_{\text{active}}} \sum_{t:\mathbb{J}_{1t}=1} q_{21t} \\ \vdots \\ \frac{1}{T_{\text{active}}} \sum_{t:\mathbb{J}_{tJ}=1} q_{2Jt} \\ \frac{1}{T_{\text{active}}} \sum_j \sum_{t:\mathbb{J}_{tJ}=1} q_{2jt} tax_t \\ \frac{1}{T_{\text{active}}} \sum_j \sum_{t:\mathbb{J}_{tJ}=1} q_{2jt} S_{jt-1} \\ \frac{1}{T_{\text{active}}} \sum_j \sum_{t:\mathbb{J}_{tJ}=1} q_{2jt} S^{\text{other}}_{jt-1} \end{pmatrix}
$$

F.2 Importance Sampling

Finding the $\hat{\theta}$ that minimizes $G_n(\theta)$ can imply many evaluations of $g(\chi_{kt}, p_{kt}, \mathbb{X}_{kt}; \theta)$. Evaluating this function implies solving the equilibrium many times. We follow Ackerberg [2009] and use importance sampling together with a change of variable, to avoid solving the game for each evaluation of the parameters. To this extent, we perturb the econometric model and add uncertainty in the production costs and the mean value of the fixed costs' distributions.

Hence, we re-write variable and fixed costs parameters as

$$
\begin{aligned}
\theta_k^{vc} &= \mu_k^{vc} + \sigma^{vc}\varepsilon_k^{vc} \\
\theta_S &= e^{\mu^S + \sigma^S \varepsilon^S} \\
\theta_R &= e^{\mu^R + \sigma^R \varepsilon^R} \\
\sigma_\varepsilon &= e^{\mu^{\sigma_\varepsilon} + \sigma^{\sigma_\varepsilon} \varepsilon^{\sigma_\varepsilon}}
\end{aligned}
$$

where $(\varepsilon_k^{vc}, \varepsilon^S, \varepsilon^R, \varepsilon^{\sigma_\varepsilon}) \sim N(0, I)$.

Under this reformulation, we re-write the objective function in terms of $\mu = (\{\mu_k^{vc}\}, \mu^S, \mu^R, \mu^{\sigma_\varepsilon})$, $\sigma = (\sigma_k^{vc}, \sigma^S, \sigma^R, \sigma^{\sigma_\varepsilon})$, and importance sampling noise ε^{IS}.

$$G_n(\mu,\sigma) = \frac{1}{T\times N}\sum_{t,k} E_{\varepsilon^{IS}} g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; \mu, \sigma, \varepsilon^{IS})' W E_{\varepsilon^{IS}} g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; \mu, \sigma, \varepsilon^{IS})$$

Although we now need to compute the expectation $E_{\varepsilon^{IS}} g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; \mu, \sigma, \varepsilon^{IS})$, we make a change of variable and use importance sampling to reduce the cost of doing so. The change of variable is such that

$$u_s^l = \mu^l + \sigma^l \varepsilon_s^l \quad l = \{\{vc\}, S, R, \sigma_\varepsilon\}$$

Let u_s be the vector of all new variables. Furthermore, let $f(u_s|\mu,\sigma)$ be the density function of u obtained by the change of variables formula, and define u's importance sampling density to be a normal distribution $N(\mu_0, \Sigma_0)$ with density function $g(u)$, which does not depend on parameters $\{\mu^l, \sigma^l\}$.

Then the simulated moment is

$$\tilde{E}_{\varepsilon^{IS}} g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; \mu, \sigma, \varepsilon^{IS}) = \frac{1}{S}\sum_s g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; u_s)\frac{f(u_s|\mu,\sigma)}{g(u_s)}$$

where u_s are draws from $g()$. Finally, we can write the importance sampling method of MSM as

$$\hat{\mu}, \hat{\sigma} = \arg\min \tilde{G}_n(\mu,\sigma) = \frac{1}{T\times N\times S}\sum_{t,k,s}\left(g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; u_s)\frac{f(u_s|\mu,\sigma)}{g(u_s)}\right)' W \left(g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; u_s)\frac{f(u_s|\mu,\sigma)}{g(u_s)}\right) \tag{33}$$

The critical aspect of Equation 33 is that u_s remains constant as μ, σ changes. Therefore, we only need to evaluate $q(p_{ft}, \mathbb{X}_t; u_s)$ S times and not for every guess of the parameters μ, σ. Instead, for each trial of the parameters μ, σ, we recompute the importance sampling weights $\frac{f(u_s|\mu,\sigma)}{g(u_s)}$, a much simpler problem.

F.3 Additional Results

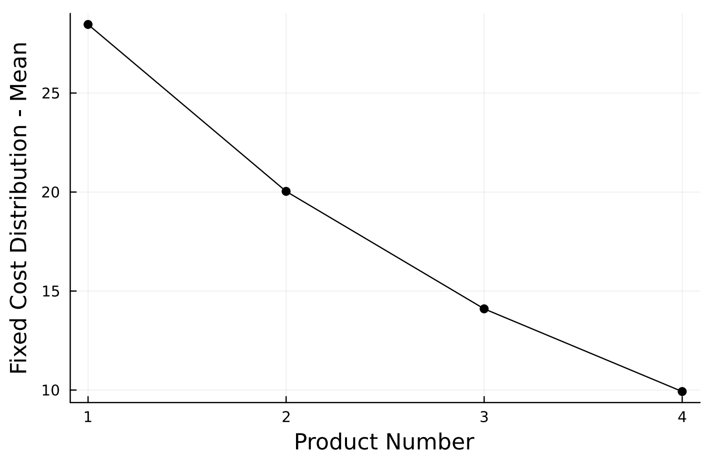
Table F.1: Parameter Estimates

	taxes	δ_t
	(1)	(2)
(Intercept)	0.243*	-0.143*
	(0.110)	(0.059)
taxes (lagged)	0.860***	
	(0.068)	
δ_{t-1}		0.007
		(0.163)
Estimator	OLS	OLS
N	44	43
R^2	0.794	0.000

Table F.2: Parameter Estimates

	θ	std
$\mu MPFlagship$	0.004	0.168
$\mu MPRegular$	0.307	0.047
$\mu MPLight$	0.168	0.065
$\mu MPSpecials$	0.001	0.064
$\mu PMFlagship$	0.109	0.094
$\mu PMLight$	0.174	0.125
$\mu PMRegular$	0.022	0.039
$\mu BATStandard$	-0.006	0.027
$\mu BATPremium$	0.182	0.169
$\mu\theta_S$	0.418	0.09
$\mu\theta_R$	40.437	44.823
$\mu\sigma_\varepsilon^2$	0.351	0.345
σ_{mc}^2	0.008	0.05
$\sigma^2\theta_S$	0.041	0.256
$\sigma^2\theta_R$	110.355	1595.918
$\sigma^2\sigma_\varepsilon$	0.026	0.114

Figure F.3: Entry Costs Shape — Returns to Scale



Note: The figure shows the average entry costs for each product, considering how many products a firm has already in the market. It is constructed using the exponential of the average values of the sampling distribution of the parameters θ_s and θ_R.

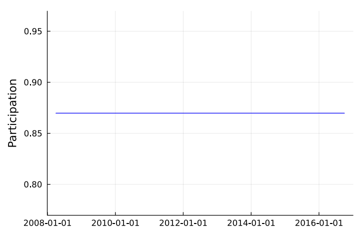
F.4 Model Fit

Table F.3: Comparison of Actual and Simulated Moments

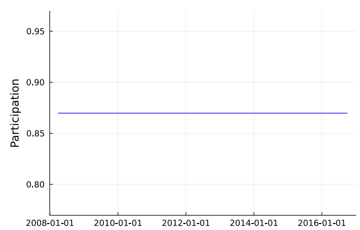
Statistics	Observed	Policies	Long-Run Simulation
Smoking Rate	0.216	0.216	0.24
AveragePrice	2.274	2.5	2.24
N Products	6.657	6.293	5.987
Switching	0.82	–	0.733
Elasticity	-0.853	–	-1.284
HHI	5782.408	–	6204.18

Note: The simulation column reflects the average across states within the stationary long-run distribution. In this column the tax process is fixed at 1.8\$$UY$.

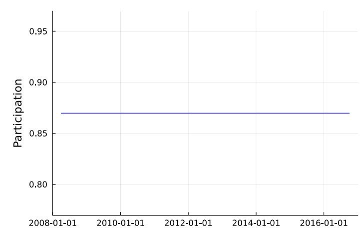
Figure F.4: Compare Observe and Simulated Participation Probabilities.



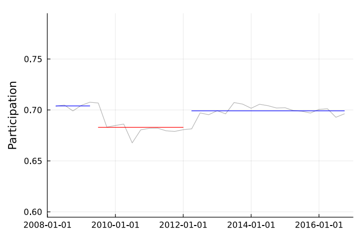
(a) Monte Paz, Flagship



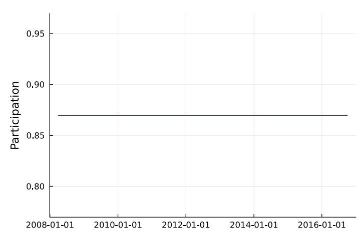
(b) Monte Paz, Other Regular



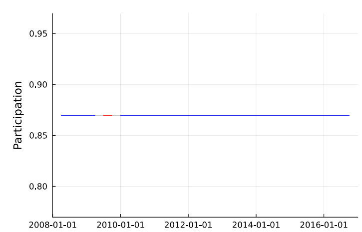
(c) Monte Paz, Light



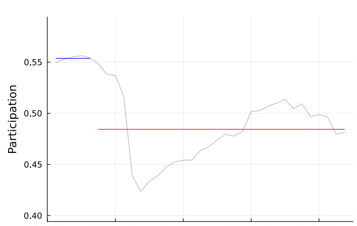
(d) Monte Paz, Specials



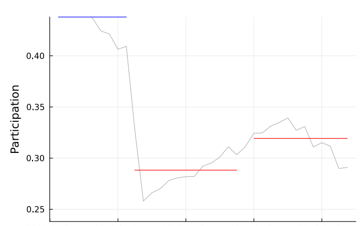
(e) Philip Morris, Flagship



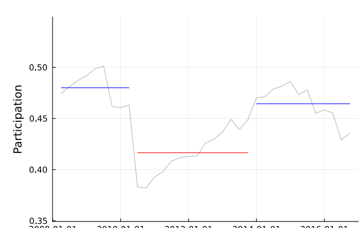
(f) Philip Morris, Light



(g) Philip Morris, Other Regular

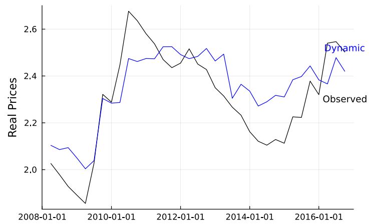


(h) BAT, Standard

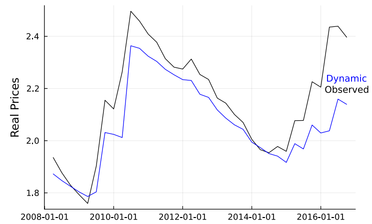


(i) BAT, Premium

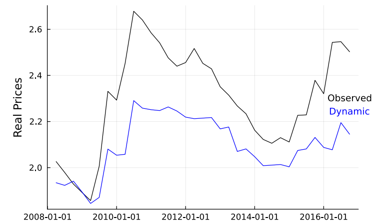
Figure F.5: Compare Observe and Simulated Prices.



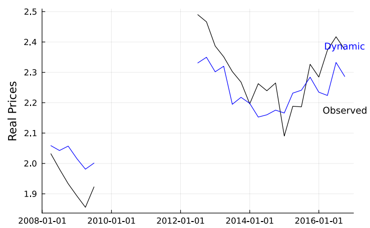
(a) Monte Paz, Flagship



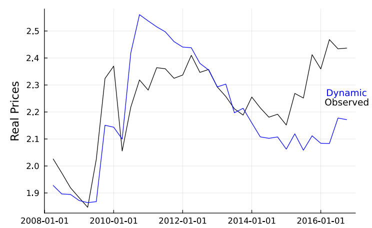
(b) Monte Paz, Other Regular



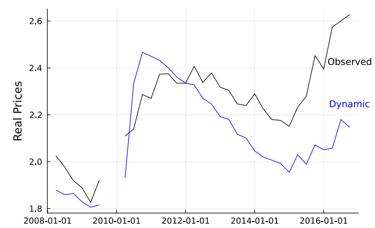
(c) Monte Paz, Light



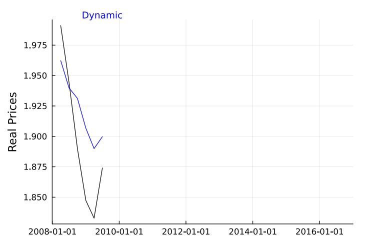
(d) Monte Paz, Specials



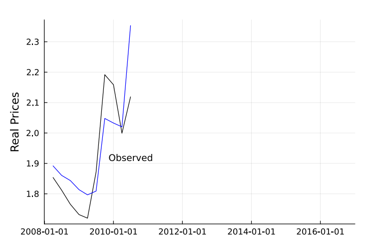
(e) Philip Morris, Flagship



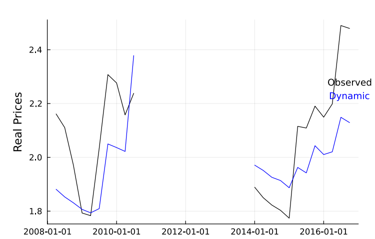
(f) Philip Morris, Light



(g) Philip Morris, Other Regular



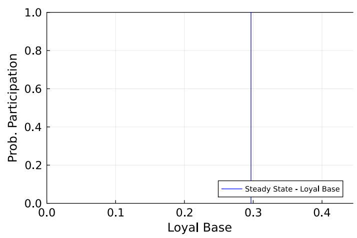
(h) BAT, Standard



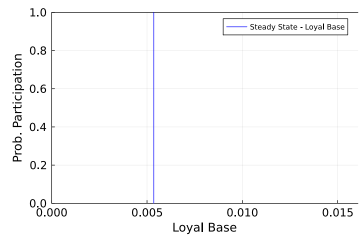
(i) BAT, Premium

F.5 Implied Equilibrium Policies

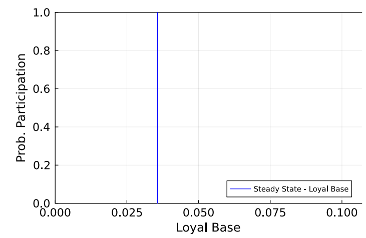
Figure F.6: Participation Policies - Low Tax



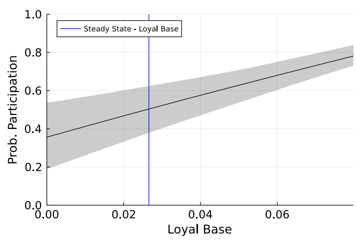
(a) Monte Paz, Flagship



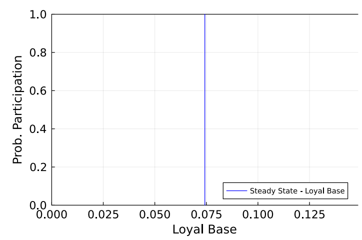
(b) Monte Paz, Other Regular



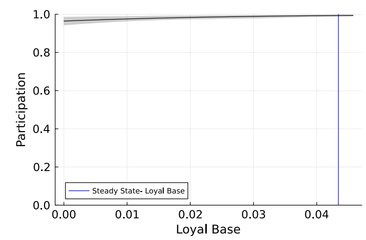
(c) Monte Paz, Light



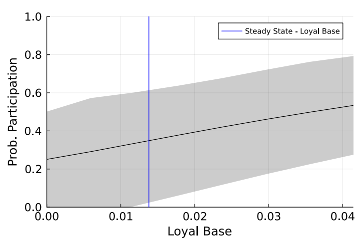
(d) Monte Paz, Specials



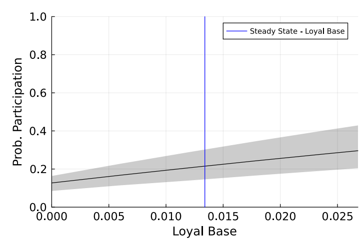
(e) Philip Morris, Flagship



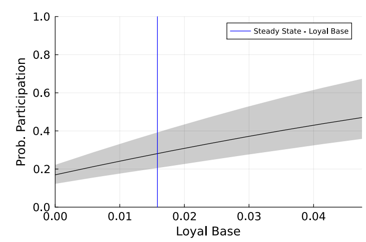
(f) Philip Morris, Light



(g) Philip Morris, Other Regular



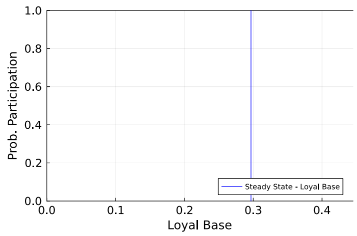
(h) BAT, Standard



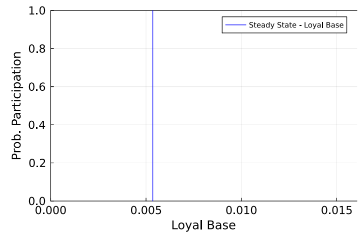
(i) BAT, Premium

Note: The policies are constructed by solving the model at the average parameters of the importance sampling distribution. This figure represents the policies when taxes are equal are equal to 1.2 U$. The vertical blue line represents the market shares/loyal base these products would obtain in a stable duopoly (without entry and exit) at constant costs equal to 1.2 U$. The shaded region indicates all the possible values that the policy might take for a given size of the product customer base. The differences are due to other products customer base.

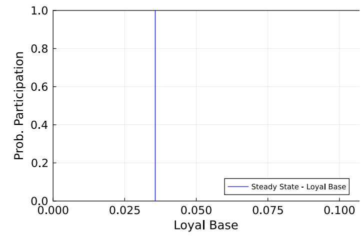
Figure F.7: Participation Policies - High Tax



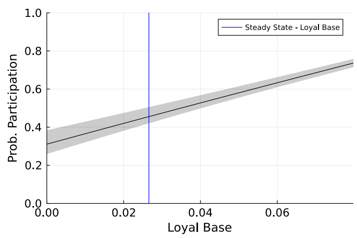
(a) Monte Paz, Flagship



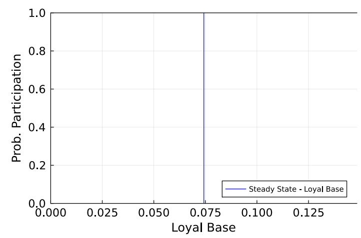
(b) Monte Paz, Other Regular



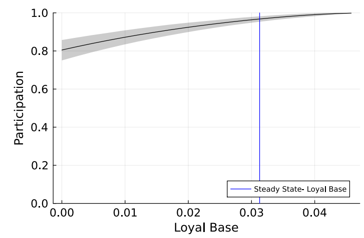
(c) Monte Paz, Light



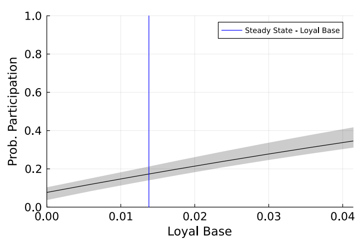
(d) Monte Paz, Specials



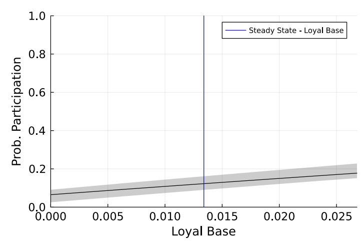
(e) Philip Morris, Flagship



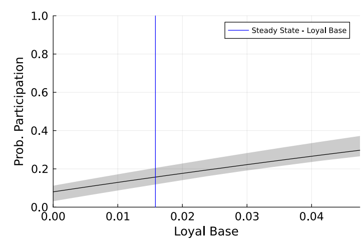
(f) Philip Morris, Light



(g) Philip Morris, Other Regular



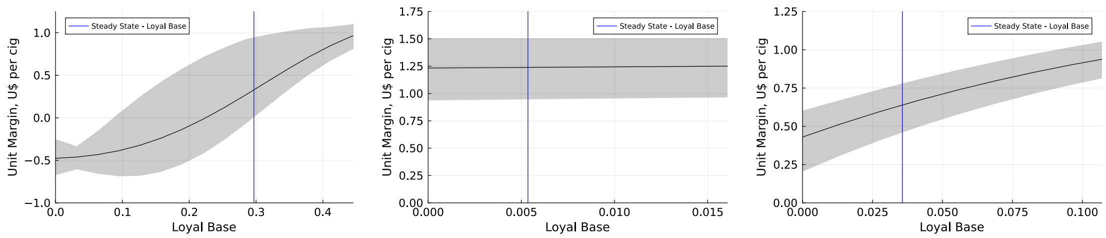
(h) BAT, Standard



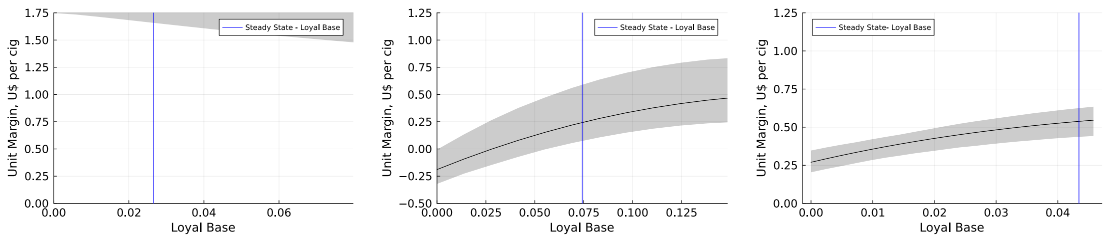
(i) BAT, Premium

Note: The policies are constructed by solving the model at the average parameters of the importance sampling distribution. This figure represents the policies when taxes are equal are equal to 2.43 U\$. The vertical blue line represents the market shares/loyal base these products would obtain in a stable duopoly (without entry and exit) at constant costs equal to 2.43 U\$. The shaded region indicates all the possible values that the policy might take for a given size of the product customer base. The differences are due to other products customer base.

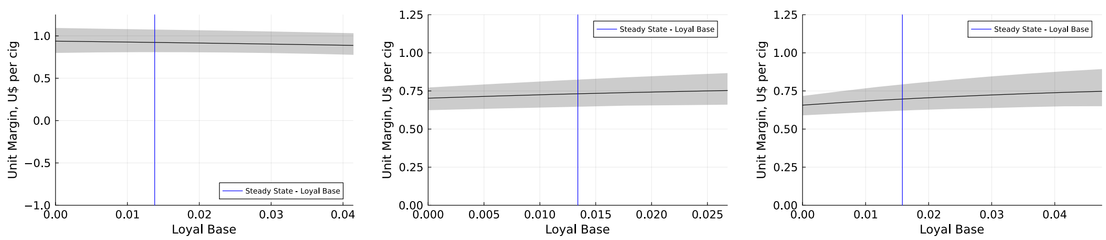
Figure F.8: Participation Policies - Low Tax



(a) Monte Paz, Flagship (b) Monte Paz, Other Regular (c) Monte Paz, Light



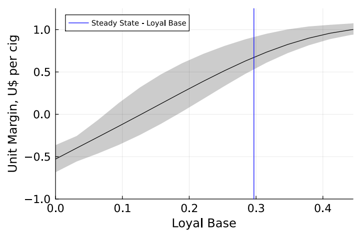
(d) Monte Paz, Specials (e) Philip Morris, Flagship (f) Philip Morris, Light



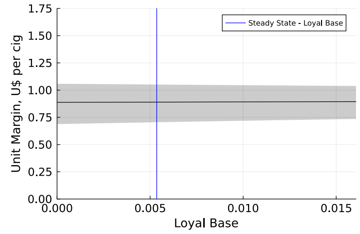
(g) Philip Morris, Other Regular (h) BAT, Standard (i) BAT, Premium

Note: The policies are constructed by solving the model at the average parameters of the importance sampling distribution. This figure represents the policies when taxes are equal are equal to 1.2 U$. The vertical blue line represents the market shares/loyal base these products would obtain in a stable duopoly (without entry and exit) at constant costs equal to 1.2 U$. The shaded region indicates all the possible values that the policy might take for a given size of the product customer base. The differences are due to other products customer base.

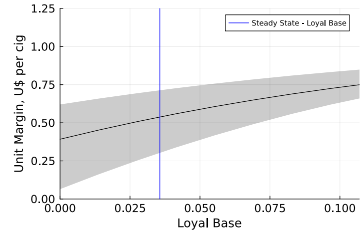
Figure F.9: Price Policies - High Tax



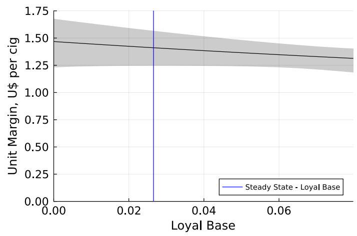
(a) Monte Paz, Flagship



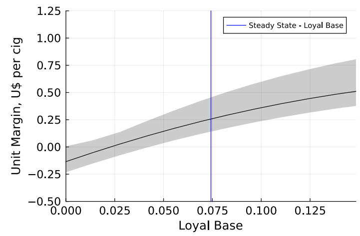
(b) Monte Paz, Other Regular



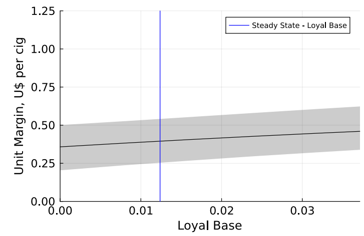
(c) Monte Paz, Light



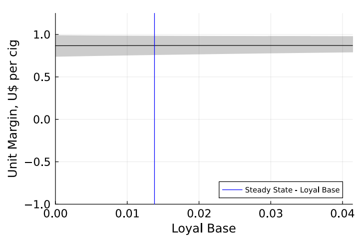
(d) Monte Paz, Specials



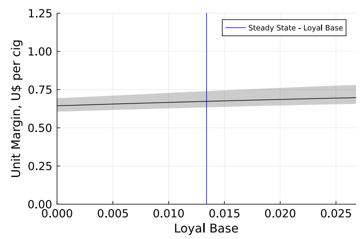
(e) Philip Morris, Flagship



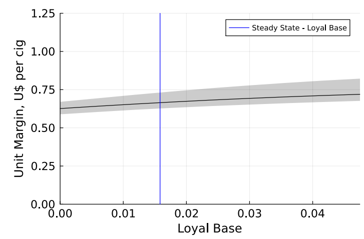
(f) Philip Morris, Light



(g) Philip Morris, Other Regular



(h) BAT, Standard



(i) BAT, Premium

Note: The policies are constructed by solving the model at the average parameters of the importance sampling distribution. This figure represents the policies when taxes are equal are equal to 2.43 U$. The vertical blue line represents the market shares/loyal base these products would obtain in a stable duopoly (without entry and exit) at constant costs equal to 2.43 U$. The shaded region indicates all the possible values that the policy might take for a given size of the product customer base. The differences are due to other products customer base.

G Appendix: Counterfactuals - Additional Results

G.1 Brand Loyalty

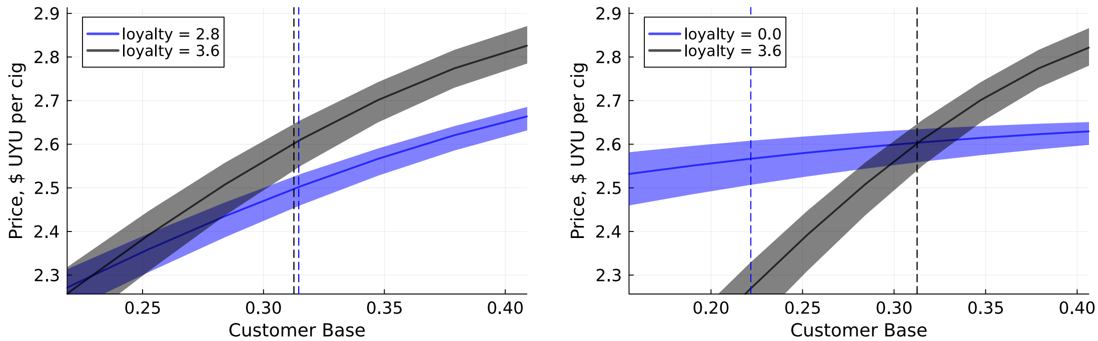
G.1.1 Non-monotonic Prices and Consumption - Further Intuition

As we modify brand loyalty, firms would also change their markups over virtual costs. Importantly, these changes are heterogeneous across products. In particular, the direct effect of lowering brand loyalty on demand crucially depends on consumers' mean valuation for the product and the size of brand loyalty. In our baseline scenario, mean valuation and brand loyalty estimates are such that consumers patronizing the market leader (Monte Paz's Flagship) return to the product with a probability higher than 90%. According to our demand estimates, small reductions in brand loyalty from the baseline do not shift the demand from returning customers down as much as it rotates out. Hence, the firm owning these highly valued products decreases prices to compensate more price-elastic locked-in customers and expand their overall sales. At the same time, the demand for products with a lower mean valuation increases because customers who chose other products last period –which are most of the customers in the market– are more likely to pick them when loyalty decreases. Thus, firms controlling these products increase their prices while their overall sales also increase. The joint effect on small loyalty contractions is to produce the initial drop in weighted average prices (the effect on products with larger shares dominates) and an increase in quantities.

When brand loyalty is not as high, the probability that consumers will repeat their choice is lower, even for products with a high mean valuation. In this case, according to our demand estimates, further reductions in brand loyalty shift the demand from returning customers down more sharply than when most past buyers return. As a result, the effect on products with a large equilibrium customer base is to shift demand down. Thus, these firms decrease prices (although not as much), and their sales decline. Now, the effect over highly valued products compensates for the increase in "smaller" products' sales and even shifts individuals to the outside option as all firms are pricing higher to invest less in attracting consumers (recall effect in Figure 14a).

Figure G.1 illustrate these different scenarios for products with high mean valuations, showing the counterfactual price policy for Monte Paz Flagship product. For intermediate levels of brand loyalty (Figure G.1a), they decrease prices when the customer base is high to compensate for the returning customers being more elastic, which reduces prices and expands their sales. When we drop brand loyalty further (Figure G.1b), the firm stops investing in attracting consumers as much, the demand from returning customers sensibly drops, and equilibrium quantities go down. However, prices do not decrease as much as in the previous case.

Figure G.1: Price Policy - Monte Paz, Flagship



(a) Price Policy - Monte Paz, Flagship

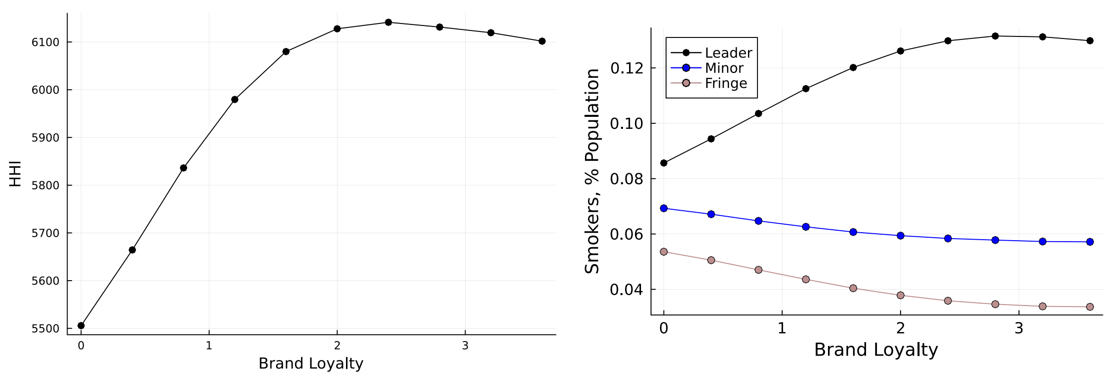
(b) Zoom in Equilibrium

Note: This figure represents the policies when marginal costs equal 1.8 U$. The shaded region indicates all the possible values the policy might take for a given size of the product's customer base. The policies are constructed by solving the model at the average parameters of the importance sampling distribution under the indicated levels of inertia. Dashed vertical lines represent the average customer base for each level of inertia.

The overall effect of reducing loyalty is to shift sales to smaller products, whose aggregate demand becomes increasingly stronger (Figure G.2a shows the distribution of sales by size of product and Figure G.2b the HHI of the industry for different levels of brand loyalty). In addition, as the virtual costs of serving consumers have increased for all products, aggregate cigarette sales drop.

G.1.2 Other Results

Figure G.2: Equilibrium Outcomes - Prices and Number of Products

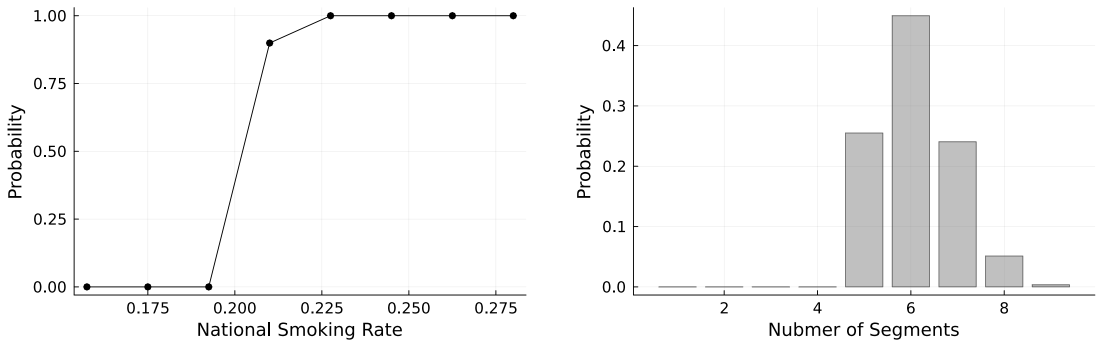


(a) Weighted average price

(b) Expected number of segments.

Note:

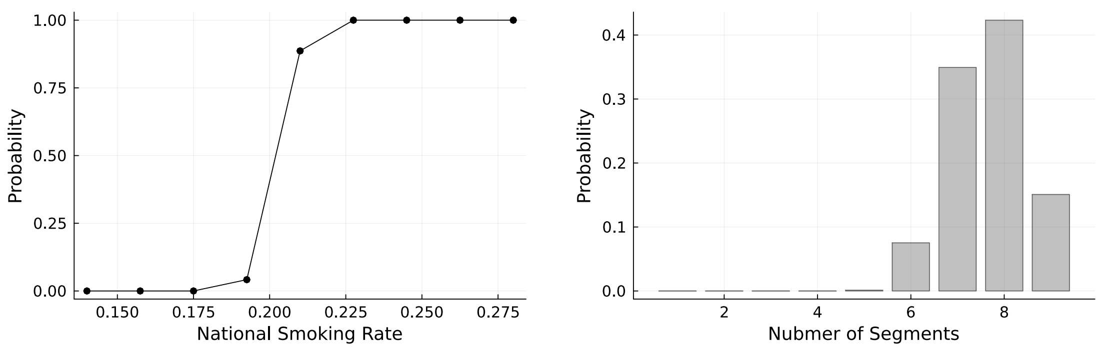
Figure G.3: Distribution of States at Baseline Estimates



(a) Distribution of Lagged Shares (b) Distribution of Products

Note: The smoking rates are assuming the total market size is 35.6%, according to the smoking rate in 2000. Moreover, we assume there is no heterogeneity in quantities smoked across different consumers.

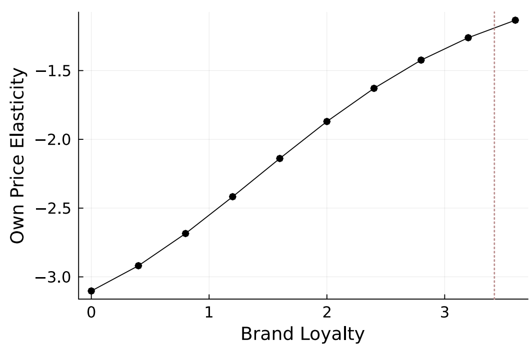
Figure G.4: Distribution of States without Brand Loyalty



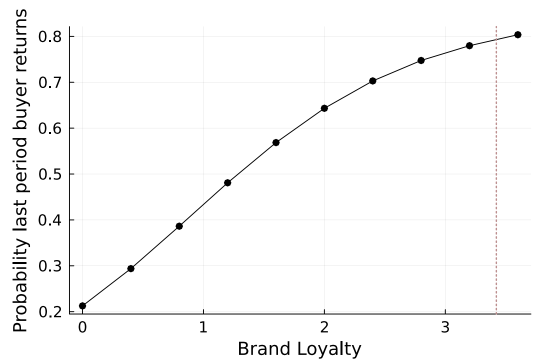
(a) Distribution of Lagged Shares (b) Distribution of Products

Note: The smoking rates are assuming the total market size is 35.6%, according to the smoking rate in 2000. Moreover, we assume there is no heterogeneity in quantities smoked across different consumers.

Figure G.5: Summary Statistics — Counterfactual Consumer Brand Loyalty



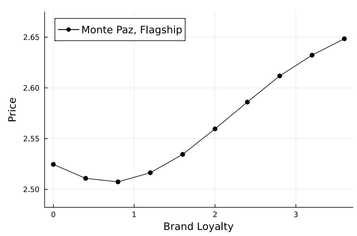
(a) Elasticity



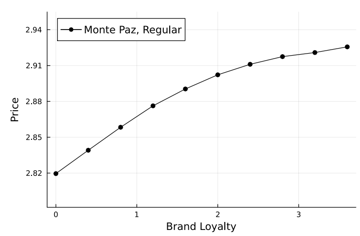
(b) Consumer Switching Behavior

Note: The figure shows each firm's average elasticity and switching behavior at equilibrium. The dotted lines represent our baseline estimates.

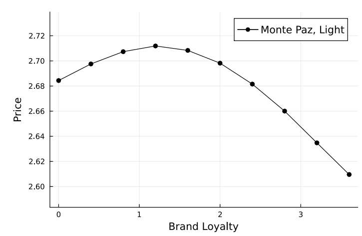
Figure G.6: Individual Prices - Counterfactual Brand Loyalty.



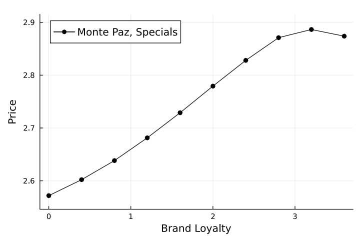
(a) Monte Paz, Flagship



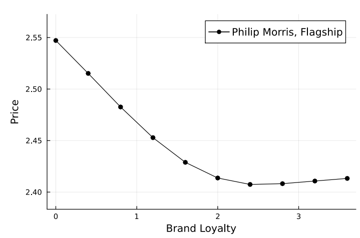
(b) Monte Paz, Regular



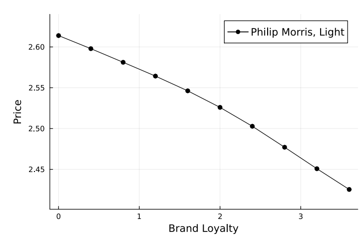
(c) Monte Paz, Light



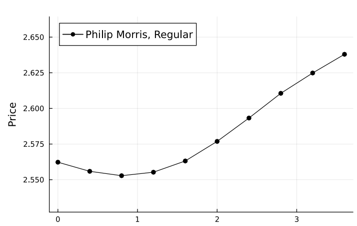
(d) Monte Paz, Specials



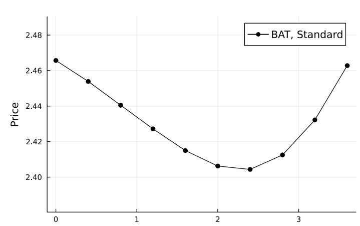
(e) Philip Morris, Flagship



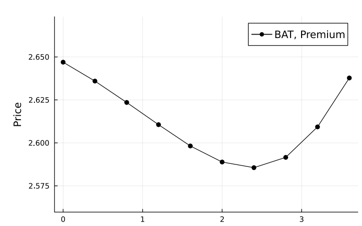
(f) Philip Morris, Light



(g) Philip Morris, Regular

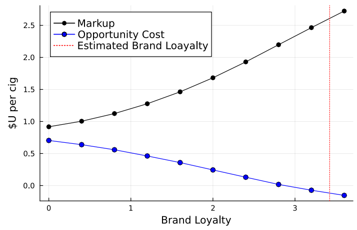


(h) BAT, Standard

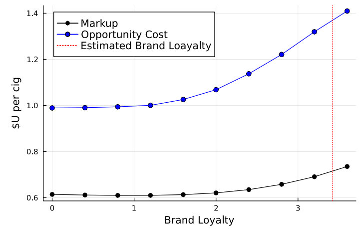


(i) BAT Premium

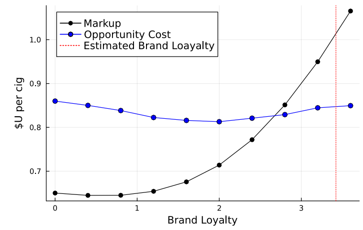
Figure G.7: Pricing Incentives – Markup v. Virtual Cost



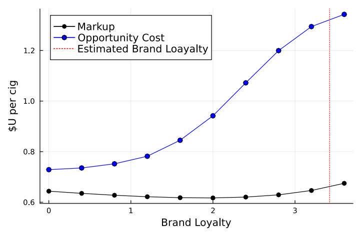
(a) Monte Paz, Flagship



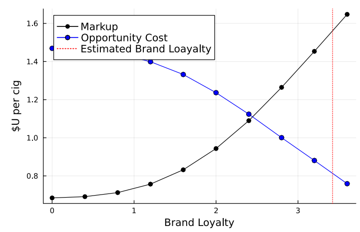
(b) Monte Paz, Regular



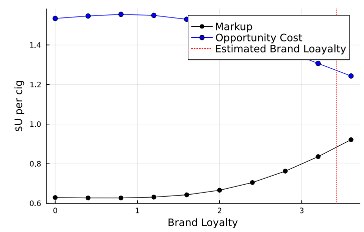
(c) Monte Paz, Light



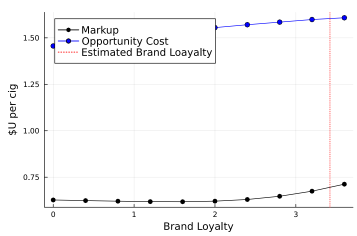
(d) Monte Paz, Specials



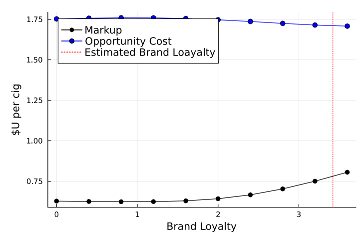
(e) Philip Morris, Flagship



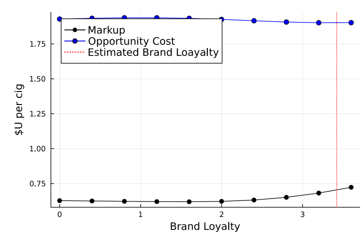
(f) Philip Morris, Light



(g) Philip Morris, Regular

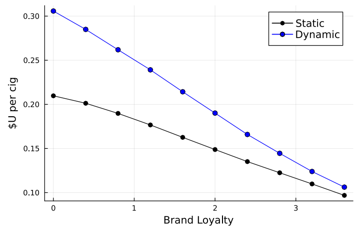


(h) Philip Morris, Light

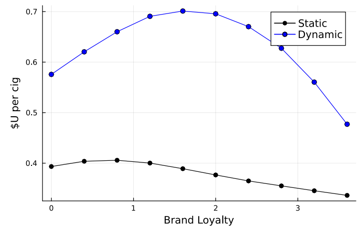


(i) Philip Morris, Regular

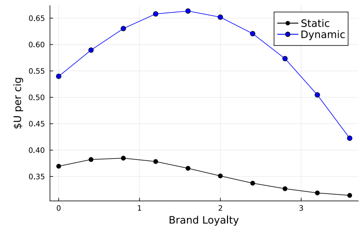
Figure G.8: Pricing Incentives — Dynamic v. static incentives within the own firm portfolio.



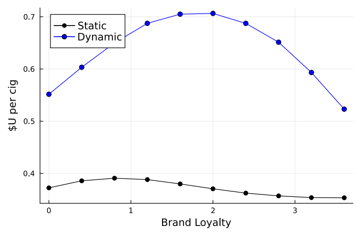
(a) Monte Paz, Flagship



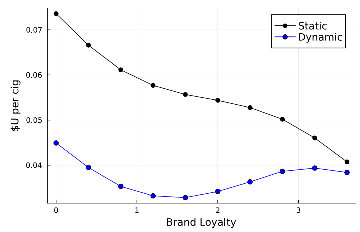
(b) Monte Paz, Regular



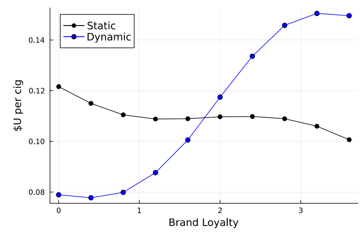
(c) Monte Paz, Light



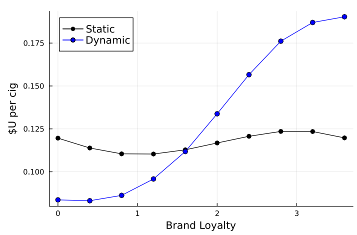
(d) Monte Paz, Specials



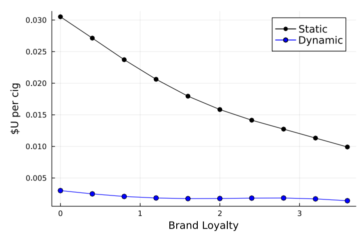
(e) Philip Morris, Flagship



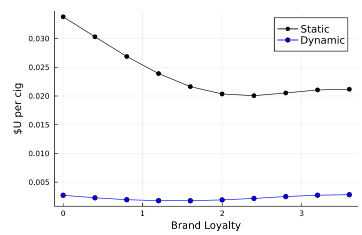
(f) Philip Morris, Light



(g) Philip Morris, Regular

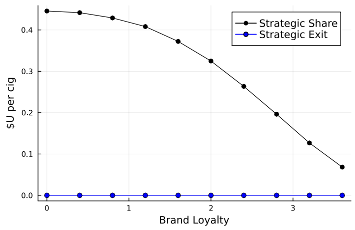


(h) BAT, Standard

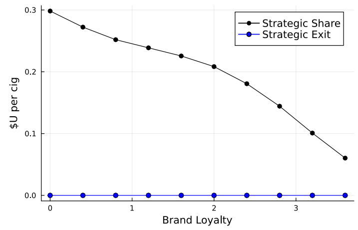


(i) BAT, Premium

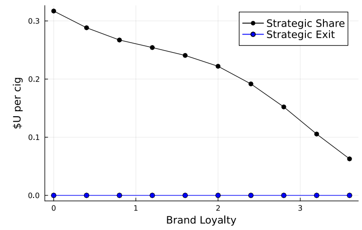
Figure G.9: Pricing Incentives — Strategic Incentives: exit inducing v. dynamic rival business stealing



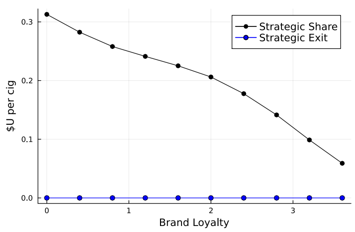
(a) Monte Paz, Flagship



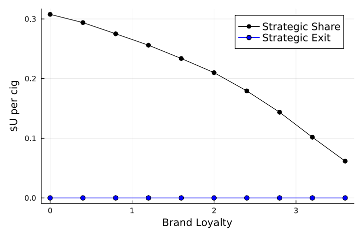
(b) Monte Paz, Regular



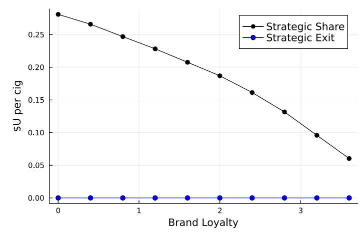
(c) Monte Paz, Light



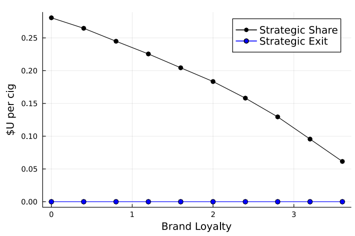
(d) Monte Paz, Specials



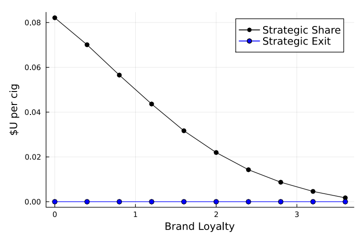
(e) Philip Morris, Flagship



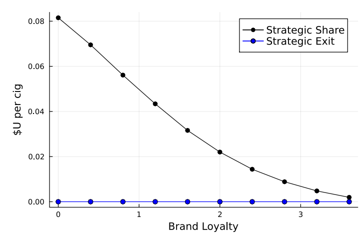
(f) Philip Morris, Light



(g) Philip Morris, Regular

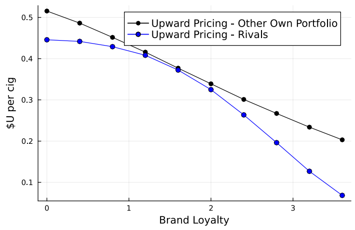


(h) BAT, Standard

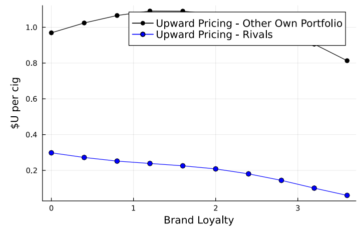


(i) BAT, Premium

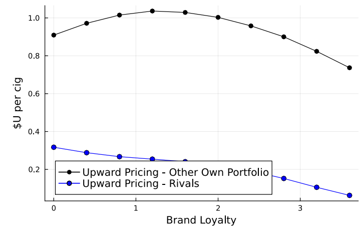
Figure G.10: Pricing Incentives — Upward pricing: Rivals versus Own.



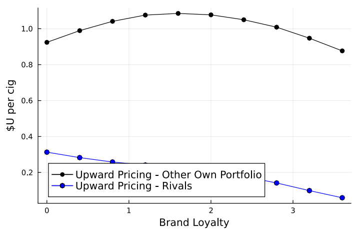
(a) Monte Paz, Flagship



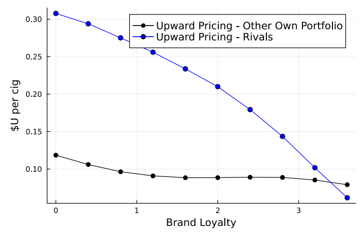
(b) Monte Paz, Regular



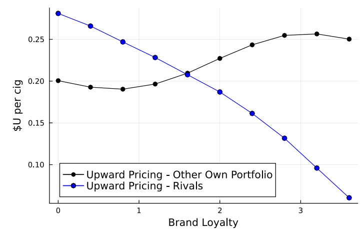
(c) Monte Paz, Light



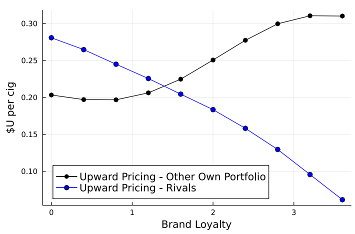
(d) Monte Paz, Specials



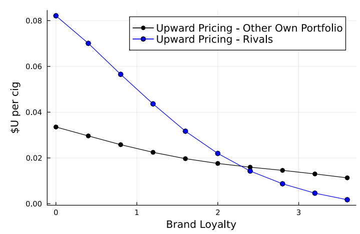
(e) Philip Morris, Flagship



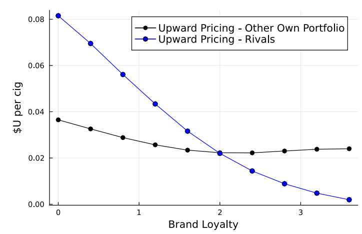
(f) Philip Morris, Light



(g) Philip Morris, Regular

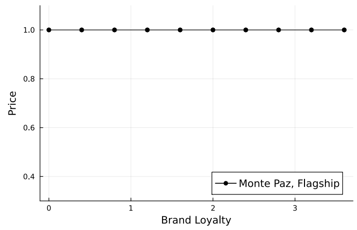


(h) BAT, Standard

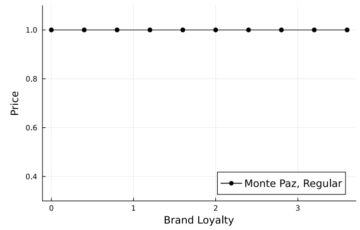


(i) BAT, Premium

Figure G.11: Individual Participation Probabilities - Counterfactual Brand Loyalty.

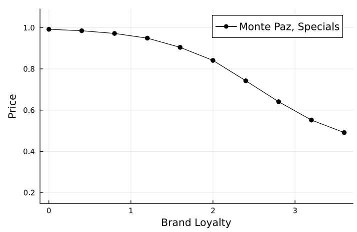


(a) Monte Paz, Flagship

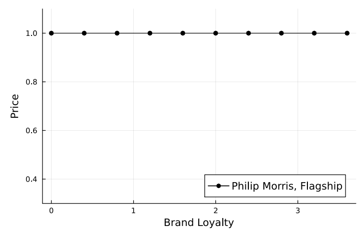


(b) Monte Paz, Regular

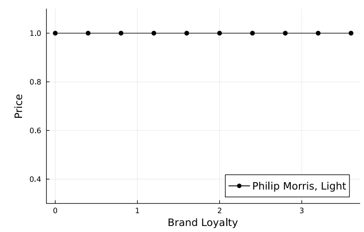
(c) Monte Paz, Light



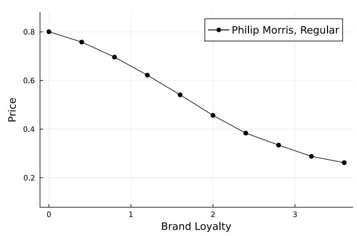
(d) Monte Paz, Specials



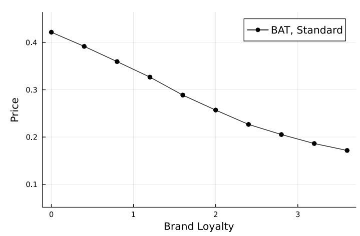
(e) Philip Morris, Flagship



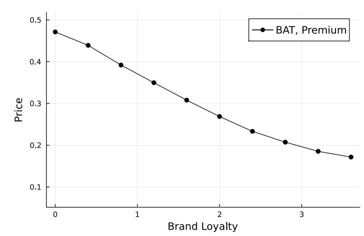
(f) Philip Morris, Light



(g) Philip Morris, Regular



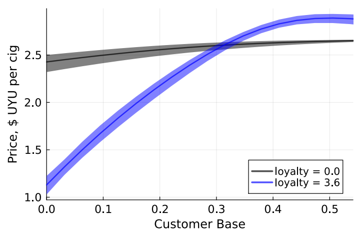
(h) BAT, Standard



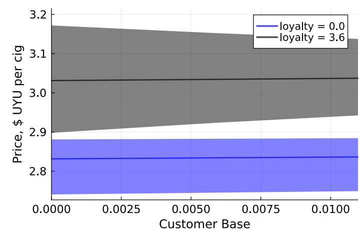
(i) BAT Premium

Participation

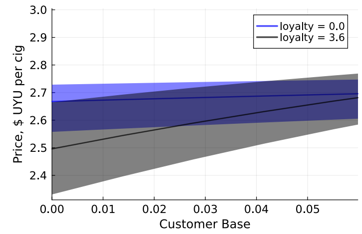
Figure G.12: Individual Price Policies, Baseline Loyalty and No Loyalty



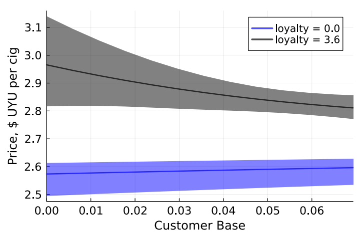
(a) Monte Paz, Flagship



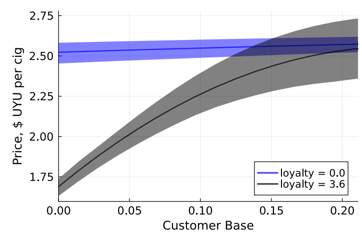
(b) Monte Paz, Regular



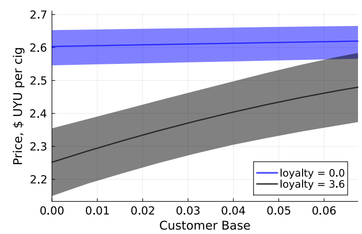
(c) Monte Paz, Light



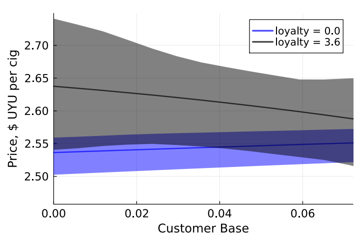
(d) Monte Paz, Specials



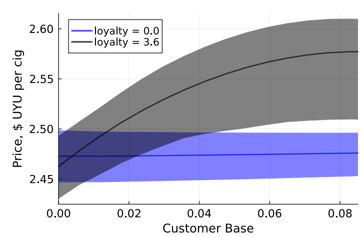
(e) Philip Morris, Flagship



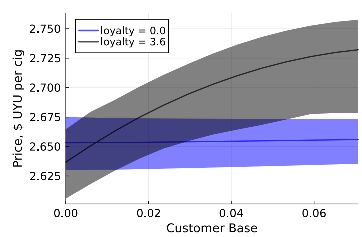
(f) Philip Morris, Light



(g) Philip Morris, Regular

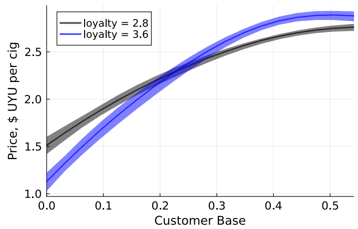


(h) BAT, Standard

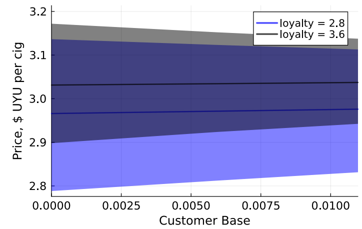


(i) BAT Premium

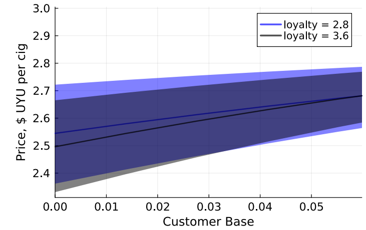
Figure G.13: Individual Price Policies, Baseline Loyalty and No Loyalty



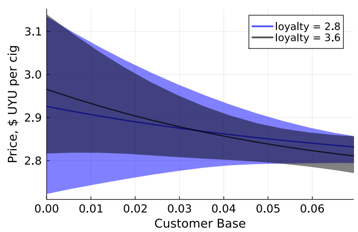
(a) Monte Paz, Flagship



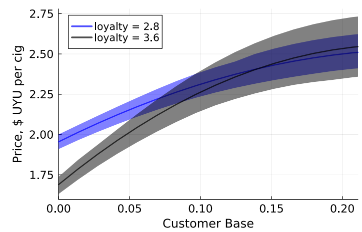
(b) Monte Paz, Regular



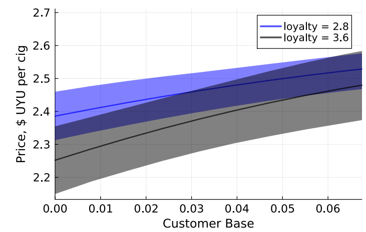
(c) Monte Paz, Light



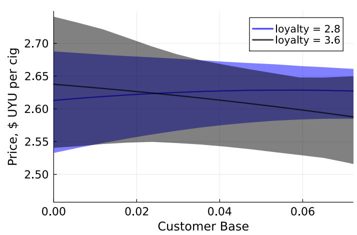
(d) Monte Paz, Specials



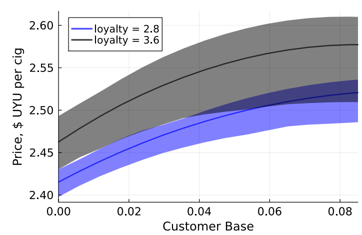
(e) Philip Morris, Flagship



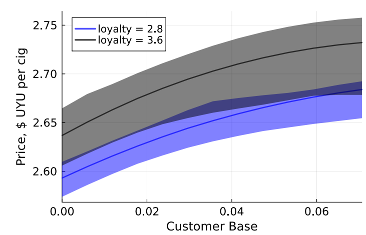
(f) Philip Morris, Light



(g) Philip Morris, Regular



(h) BAT, Standard

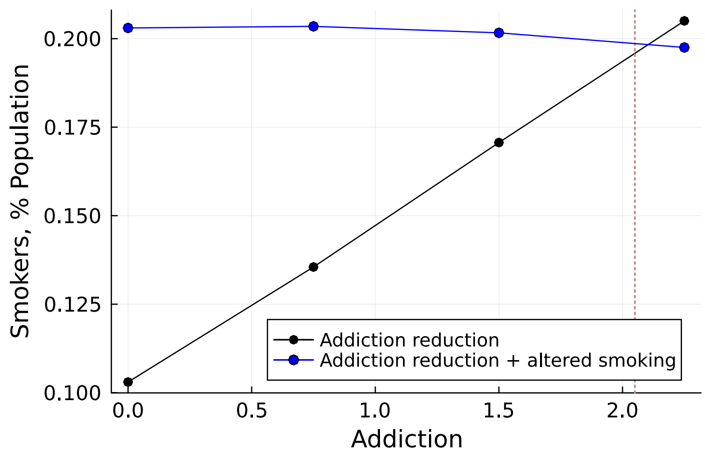


(i) BAT Premium

Policies

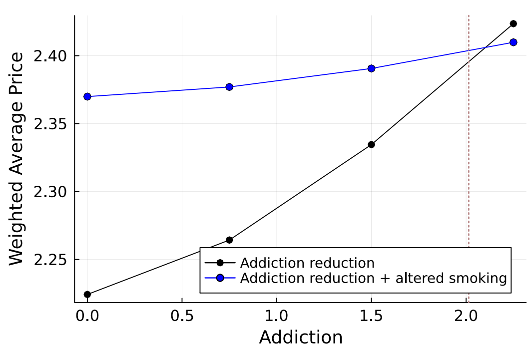
G.2 Addiction

Figure G.14: Equilibrium Consumption - Eliminating Inertia with countervailing effects

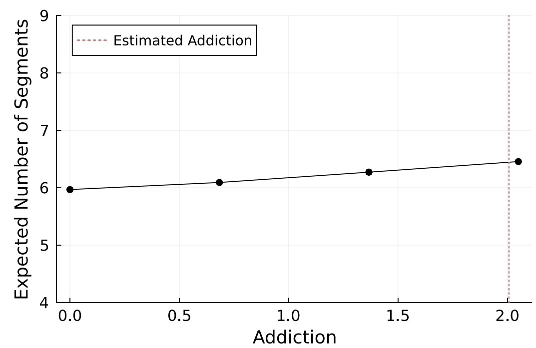


Note:

Figure G.15: Equilibrium Outcomes - Prices and Number of Products



(a) Weighted average price



(b) Expected number of segments.

Note: