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Abstract

Chapter 1: Curbing Habit Formation: The Effects of Tobacco Control Policies in a Dynamic Equilibrium

(with Gastón López)

We study the equilibrium effects of tobacco control policies. To accurately assess the impact of tobacco regulation on consumption, it is essential to anticipate firm responses. 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 smokers have significant addiction and brand loyalty. We then propose a tractable equilibrium notion to compute market outcomes and show that dynamic competition models under inertia capture firm behavior well. We use this framework to examine the counterfactual effect of caps on nicotine concentration and uniform packaging, which are expected to decrease smokers' addictiveness and brand loyalty, respectively. We highlight that firms' price and portfolio responses account for a substantial part of the policies' impact. Moreover, more simplistic models of static competition would have led to significantly different conclusions about expected companies' responses.

Chapter 2: Dynamic Equilibrium Effects of Sin Taxes for Addictive Products

I study the effects of addiction in the design of sin taxes. I highlight that the addictive properties of sin goods make the intensive margin of consumption more salient, which modifies the curvature with respect to traditional unit demand models. Moreover, I show

that the relationship between curvature and pass-through is also affected by addiction because firms consider the long-term implications of their pricing decisions. In this context, the pass-through is determined by the relative change in the incentives to harvest current consumers and invest in future sales as taxes increase. Finally, I show how the demand and supply dynamics introduced by addiction significantly affect optimal taxes and incidence in the tobacco industry.

Chapter 3: How Do Governments Engage in Price Discrimination? Evidence from a Large-Scale Nationalization

(with Gastón López)

State-owned enterprises (SOEs) have the potential to correct market failures, but they are also subject to the influence of politics and interest groups. We examine how this trade-off affects pricing decisions in the context of the nationalization of the leading gasoline company in Argentina. Descriptive analysis suggests that pricing patterns changed after the nationalization. First, the government exerted less market power, charging lower prices on average. Second, it engaged in less *economic price discrimination*, reducing the correlation between prices and consumers' willingness to pay. Third, it engaged in *political price discrimination*, charging lower prices in provinces with political connections with the state-owned firm. We develop and estimate a model of gasoline supply and demand under market power and recover the government's objective function. We find that the nationalization is associated with lower markups, but also with politically motivated redistribution. Compared to a benevolent planner–that internalizes the welfare of all consumers and firms equally–the government sets prices as if it targets specific groups: middle-income households and households in provinces with political connections. Lastly, we study the company's response to policy alternatives, including pricing rules that are in place in SOEs worldwide. Our findings show that these rules effectively reduce the influence of politics in pricing but are associated with higher costs: they reduce overall welfare by 3% and increase the taxpayers' burden, reducing the SOE's profit by 4%. These findings emphasize the importance of politics in shaping governments' decisions and the role of SOEs as instruments for redistribution.

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Chapter 1

Curbing Habit Formation: The Effects of Tobacco Control Policies in a Dynamic Equilibrium

1.1 Introduction

Tobacco kills 8 million people every year around the world and more than 480,000 in the US alone. Although governments have discouraged its consumption through taxation and regulation, 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 decrease 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 warned that uniform packaging could "reduce brand loyalty, causing smokers to switch

[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.

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 have two well-known sources of habit formation. They become *addicted* to tobacco due to nicotine intake and develop persistent *brand loyalty* to the products they smoke.[2] Under these forms of habit formation, future consumption becomes a function of current purchases. Thus, firms have incentives to consider the long-term implications of their decisions. The economic literature has highlighted that such incentives modify how firms price and offer products. For instance, Klemperer (1987a) found that consumer inertia encourages firms to lower prices to attract a larger customer base and then raise them to profit from the locked-in consumers. Also, the sacrifice of profits 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. Therefore, a careful analysis of tobacco regulation must account for and evaluate firms' dynamic incentives.

To empirically assess the equilibrium effects of regulation in tobacco markets, we develop and estimate a dynamic model of competition that accounts for consumers' and firms' responses. Consumers exhibit addiction and brand loyalty, while forward-looking firms choose prices and product portfolios. We apply this model to the Uruguayan cigarette industry and provide robust empirical evidence that a dynamic competition model is necessary to capture firm behavior realistically. Finally, we simulate the equilibrium effect of the FDA's nicotine caps and uniform packaging, two policies expected to decrease the degree of habit formation in the industry. We find that curtailing consumers' habit formation is an effective

[2]Product loyalty is significantly higher in the tobacco industry than for other consumption goods. US consumers make 60% of cigarette purchases on their focal product (Dawes, 2014), while the average across products is approximately (29-33)% (Uncles et al., 1994; Bhattacharya, 1997).

tool to curb tobacco consumption and that firms' responses account for a substantial part of the overall effect. Our results suggest that these policies discourage firms from capturing new consumers by restricting their ability to retain them in the future, which tends to reinforce the direct effect. More simplistic models of static competition would have missed these dynamic considerations and led to different conclusions since demand also becomes substantially more elastic.

Connecting our model to the data involves not only identifying its primitives but also overcoming significant computational constraints. To identify its primitives, we combine product-level data and a panel of smokers with rich variation from the Uruguayan experience. We leverage two primary sources of variation to identify consumers' addiction and brand loyalty. First, there are notable tax oscillations.[3] Tax-driven price swings allow us to observe asymmetric responses to prices of consumers with and without dependence, which informs the extent of addiction. Second, a regulation forbade firms from offering multiple products under the same brand name and forced approximately 40% of products out of the market. The choices of customers who "lost" the product to which they were loyal identify the preferences of consumers who are not used to any particular product but still face addiction. To alleviate the computational constraints, we propose a tractable equilibrium concept that restricts firms' informational requirements. While such restrictions make the equilibrium easy to compute, they preserve several key strategic incentives that arise in the Markov Perfect Equilibrium (MPE). The computational simplicity of the equilibrium enables the application of the method of simulated moments (MSM) to estimate costs.[4]

[3] These fluctuations arise from (1) governmental priority shifts regarding tobacco control and (2) setting specific taxes at nominal values.

[4] 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. However, participation choices and prices define distinct combinations of marginal cost and continuation probabilities that could rationalize them. Therefore, conduct still aids identification.

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; Tuchman, 2019). The estimated production costs are small, implying that taxes represent more than 90% of firms' total marginal costs. Under these conditions, firms' dynamic and strategic incentives play a critical role in determining industry dynamics. For instance, we find that firms avoid lowering prices too much to prevent stealing consumers from rivals and sparking fiercer competition in subsequent periods. Our estimates suggest this form of business-stealing is comparable to the business-stealing effect within the firm portfolio.

Next, we provide evidence that our theoretical model of competition under inertia captures firm behavior realistically. The model explains two market features that would be hard to capture in a static competition model. First, it explains why firms set low markups despite highly inelastic demand. Indeed, the fact that firms are pricing in the inelastic region of the demand curve already suggests that a static model cannot accurately depict firm behavior. In our dynamic competition model, firms internalize consumers' contribution to their *long-term* profits. Therefore, firms are willing to sacrifice short-term profits to retain and attract new customers. As a result, they set lower markups than those implied by a static model for any elasticity level. Second, under the estimated levels of habit formation, 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–are similar and not caused by cost changes or consumer preferences.

Finally, we use our framework to simulate the counterfactual effect of nicotine caps and uniform packaging. We find that supply responses are relevant to understanding the impact of both policies. The common feature of these policies is that they lower consumers' habit formation, addictiveness, and brand loyalty respectively. Although lowering inertia increases demand elasticity substantially (up to three times in some policy scenarios), it also reduces the long-term value customers have for the firm. Thus, firms lower their investments in bringing new customers to the market, constraining price decreases and reducing consumption. We show this effect is equivalent to raising firms' costs. Nonetheless, declines in consumer inertia can facilitate the introduction of new products. If the policy shifts demand towards less attractive products without directly affecting the aggregate market, as with uniform packaging, disadvantaged products can generate more profits. Moreover, endogenous entry cost decreases because stealing consumers from established products becomes more accessible. As a result, product availability and consumption can increase.

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–is a valuable tool to limit consumption. Unlike taxation, it can reduce consumption without increasing the burden on consumers, which makes it especially attractive for regulators.

Related Literature We contribute to the policy literature on tobacco control, understanding industry dynamics under consumer inertia, and the methodological body of work on empirical dynamic oligopolies. From the policy point of view, while many studies have investigated the effect of multiple tobacco regulations, ours is one of the few studies accounting for firm responses and industry dynamics.[5] Different from previous work, we compute tobacco firms' equilibrium price and portfolio strategies within an empirical dynamic oligopoly.

[5] 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.

In that sense, our work also relates to Barahona et al. (2023), which accounts for firms' responses to evaluate the equilibrium effect of food labeling policies, and Abi-Rafeh et al. (2023), which analyzes firms' dynamic incentives to study the impact of sin taxes and advertisement restrictions in the sugar-sweetened beverage industry. Our results support using non-price policies to reduce sin-goods consumption, as they can achieve their goals without shifting the burden to consumers, which can have negative distributional consequences, as recently illustrated by Conlon et al. (2022).

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), and introduce entry and exit considerations following the framework laid out by Benkard (2004); Farrell and Katz (2005); Besanko et al. (2014, 2019) to study games of dynamic competition under learning-by-doing, and network externalities. 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.[6] Similar to previous studies, we find a non-monotonic relationship between prices and brand loyalty.[7] Our work suggests this pattern remains even after introducing entry and exit decisions. Finally, our estimates indicate that firms do not engage in entry-deterrence or exit-inducing behavior despite having rational incentives to do so, as initially noted by Klemperer (1987b) and recently incorporated into a legal theory of predation (Fumagalli and Motta, 2013).

We also relate to many empirical papers taking models of consumer inertia to the data. Our central contribution to this empirical literature is to provide direct evidence that firms are forward-looking and behave close to theory predictions. Our approach is reminiscent of

[6]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.

[7]This relation appears to be a robust feature of competition under inertia and aligns with most of the literature, both when the seller cannot discriminate between consumers (Dubé et al., 2009; Arie and E. Grieco, 2014; Fabra and García, 2015) and when they do (Cabral, 2016).

Benkard (2004), which estimates all primitives of the model without ever solving the equilibrium and then compares equilibrium outcomes with data. Although we use the equilibrium 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. Regarding our identification and estimation strategy, price oscillations have been previously used to identify switching costs (Pakes et al., 2021) and brand loyalty (Dubé et al., 2010), while transitory shocks to the choice set have also been used to identify switching cost and inattention (Handel, 2013). We also relate to a smaller literature estimating costs in dynamic models of price competition. 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; Pavlidis and Ellickson, 2017).

Finally, we contribute to expanding the empirical tools available to analyze dynamic oligopolies. Recent work has stressed the limitations of MPE for empirical work. In response, Weintraub et al. (2008); Fershtman and Pakes (2012); Benkard et al. (2015) and Ifrach and Weintraub (2017), among others, have proposed relaxations of the MPE, which allow for tractable computation of equilibria. A common feature of these approaches is that they are applied to games that restrict firms' dynamic controls to affect their own states only. Hence, assuming rivals' states are fixed at some stationary level as is the case of Weintraub et al. (2008) or evolving according to a quasi-exogenous process as in Ifrach and Weintraub (2017), does not eliminate many of the relevant strategic incentives present in the MPE of these games. However, in several dynamic games of price competition, such as competition under inertia, network externalities, and learning-by-doing, firms' dynamic strategies (prices) affect all player's states' transitions (demand). This interaction, in turn, gives place to rich strategic incentives and industry dynamics–see, for instance, Farrell and Katz (2005); Besanko et al. (2010, 2014). Our approach is innovative in that it preserves these strategic interactions while still being tractable. To achieve this tradeoff, we must limit firms' strategic incentives to be homogeneous across rivals or groups of rivals.

1.2 Industry Background

Next, we describe the Uruguayan tobacco market. We observe that consumer choices are persistent. Moreover, we argue that firm behavior is consistent with a model of competition under habit formation, a point we revisit in Section 1.5.3.

1.2.1 Data

We use two primary 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. The market structure is simple. Three players participate in the Uruguayan cigarettes market.[8] 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.

[8]Observe that we are excluding three potentially relevant substitute products. First, we exclude roll-your-own tobacco products. Second, we are also omitting the smuggled cigarette products. Finally, note that our sample period coincides with the rise of e-cigarette sales in the US (Tuchman, 2019). However, Uruguay forbade the commercialization of e-cigarettes. 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.

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. Initially, the panel included only smokers, but if they decided to quit between interviews, they stayed in the sample. This panel contains information about 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. 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. Appendix A.1 summarizes this information and presents the details of the product aggregation.

1.2.2 Addiction and Brand Loyalty

Table 2.1 shows the proportion of consumers who repeat choices across waves of the individual panel. 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. 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, to which we come back in Section 1.4.

1.2.3 Investing and Harvesting

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

		Repeat Choice	Smoke
Smoker Status	Year		
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

Note: Probabilities are computed between waves of the ITC survey, which usually span over two years.

Table 1.1. Switching matrix for smokers and non-smokers

places, and imposing sizeable pictorial health warnings on tobacco products' packaging. In 2009, the government passed the "one-presentation-per-brand" regulation, which required producers to use a different brand name for each product (see DeAtley et al. (2018) for a detailed analysis of the policy compliance). 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.

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. For instance, Philip Morris had to discontinue sub-varieties of the Marlboro brand, which accounted for more than 25 % of total sales.[9] 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

[9]Informal talks with industry agents suggest that international property rights agreements delayed the introduction of new brands to the country. Philip Morris International 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. See Figure A.1.5 for a representation of how it affected Philip Morris' portfolio. The Uruguayan government finally won the case, and the norm remains.

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 1.1 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.

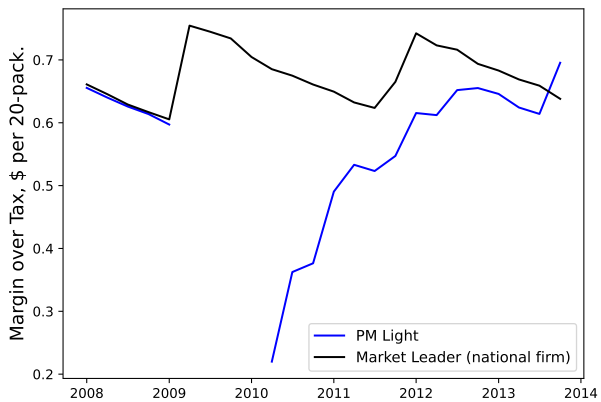


Figure 1.1. Philip Morris' real unit margin.

Note: The unit margin is computed against the taxes. It does not include any other marginal costs the firm might have while producing cigarettes. 25% of the drop was due to nominal price drops, while the other 75% was due to tax increases not passed to prices.

We stress that firms' responses to the policy are consistent with investing in consumers in a model of competition under habit formation. 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, it would require artificial, often implausible, cost changes to justify introducing new products by pricing them at cost, as in Figure 1.1. However, if consumers are state-dependent, firms can affect future demand by changing prices today, which appears consistent with firms' aggressive penetration pricing strategies.

1.3 A dynamic model of competition under inertia

This section presents a dynamic competition model for consumers with addiction and product loyalty. To simplify notation, we assume firms produce one product. In the general model, a fixed number of firms make portfolio and pricing decisions. Although the extension to multi-product firms is almost immediate, we stress any additional assumption when required. Section 1.3.2 analyzes firms' equilibrium behavior focusing on a pure strategy Markov perfect equilibria (Maskin and Tirole, 1988). In Section 1.3.3, we present an alternative, empirically tractable equilibrium concept.

1.3.1 Model Setup

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 $\mathcal{J}$, 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 period t chooses a single product or the outside option–not to smoke. Consumers have endogenous, time-varying, individual preferences. Utility depends on the state $z \in \{1, ..., N\}$, i.e., the product they patronize, or $z = 0$ if they were not smoking the previous period. Consumer i's utility from consuming product j in market t, if she was in state z, is

$$\begin{aligned} u_{ijt}(z,\mu^D) &= \delta_t + \delta_j + \sum_r \sum_k (D_i^r X_j^k)\gamma^{kr} + \eta_0 1\{z \neq 0\} + \eta_1\{z = j\} + \epsilon_{ijt} \quad \text{if } j \neq 0 \\ u_{i0t}(z,\mu^D) &= \epsilon_{i0t} \quad \text{otherwise} \end{aligned} \tag{1.1}$$

$\sum_r \sum_k (D_i^r X_j^k)$ 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. δ_t is the mean valuation for cigarettes in period t, δ_j is product j's mean utility. 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". μ^D summarizes all consumer preferences: $\mu^D = (\delta_t, \delta_j, \gamma^{kr}, \eta_0, \eta_1)$. ϵ_{ijt} is a type I extreme value error term.

Under these assumptions, today's choices depend on the decisions of the previous period. 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, $\mathbb{J}_t$. Note that the demand depends on the whole vector of market shares for each product by each type of consumer. This dependence is essential to define the states of the game and suggests it grows exponentially with the number of products and consumer types. Letting M be the market size, which we fix throughout time, we can write the demand for product f at time t as $D_{ft}(p_t, S_{t-1}, \mathbb{J}_t; \mu^D) = M \times S_{ft}(p_t, S_{t-1}, \mathbb{J}_t; \mu^D)$

Discussion - Consumer Preferences We simplify consumer preferences in three dimensions. First, we depart from classic rational addiction models (Becker and Murphy, 1988) in two ways: individuals are myopic and do not experience heterogeneous dependence on cigarettes due to the intensity of past consumption. Our assumption about myopic consumers is not uncommon in the literature –see, for instance, Tuchman (2019)– and it arises from the challenge to differentiate it from forward-looking behavior empirically.[10] Moreover, Arcidiacono et al. (2007) shows that the distinction between myopic and forward-looking behavior has almost identical implications for the estimation of addiction. Our counterfactuals focus on reducing addictiveness and brand loyalty. Thus, the myopic model approximates consumers' behavior well, even if it does not capture the underlying mechanism. Our assumption about homogeneous addictiveness is empirically supported. Although we would have expected long-term consumers or heavy smokers to be less likely to quit, our data does not show significant heterogeneity in quitting rates (or product switching) across the age profile of smokers or the time smoking.[11]

Second, we model demand as a discrete choice process despite the intensive margin having a relevant role in cigarette consumption. Although the intensive margin is relevant to accurately characterize the demand and policy evaluation, accounting for the intensive margin would significantly expand the model's state space. In that case, firms would have to track the entire distribution of consumption. Third, we assume there is no unobserved persistent preference heterogeneity. Introducing unobserved persistent heterogeneity would also increase the size of the state substantially as it expands the number of consumer types to evaluate. We have chosen to follow this simplistic demand representation because it can still capture firm behavior well, which is the primary objective of our work. The fact that we can accurately represent firm behavior suggests that, in practice, companies might only track some naive approximations of consumer heterogeneity. For instance, not accounting

[10]There is, however, some evidence in favor of rational addiction (Becker and Murphy, 1988; Chaloupka and Warner, 2000; Gruber and Köszegi, 2001; Arcidiacono et al., 2007)

[11]Table B.1.1 presents linear regressions confirming these results. There is, however, some heterogeneity in the amount of cigarettes consumed in the past.

for unobserved persistent preferences might imply that we incorrectly assign some choice persistence to state-dependent utility. However, if firms made similar "mistakes", our model would still be a good approximation of the actual market dynamics.[12]

Variable Profits Prices, demand, and marginal production costs (c_{ft}) determine per-period profits $\pi_f(p_t, S_{t-1}, \mathbb{J}_t, c_{ft}, \mu^D) = (p_{ft} - c_{ft})D_{ft}(p_t, S_{t-1}, \mathbb{J}_t; \mu^D)$. 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

[12]This observation highlights the usefulness of considering firm behavior to separately identify unobserved persistent preference from structural state dependence. We leave the exploration of this idea for future research.

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.

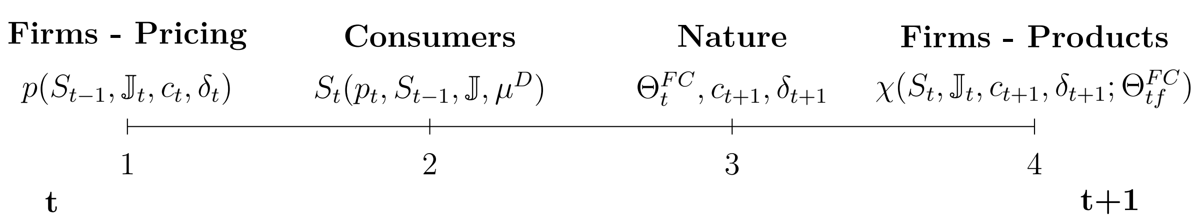


Figure 1.2. Stage Timeline

Our timing assumption is similar to Besanko et al. (2014) and differs from several papers in the literature, such as Wollmann (2018) and Fan and Yang (2020). While the latter papers intend to highlight the effect that product positioning has on subsequent pricing effects, we focus on the dynamic incentives that firms have to price. Among these incentives, we want to characterize the possibility of excluding rivals' products from the market, which our timing assumption allows us to do.[13]

[13]Our interest in the exclusionary effects of pricing is motivated by the fact that tobacco companies have

Transition Dynamics Today's prices, past market shares, and the current choice set determine the next period's customer base. That is, $S_{ft} = S_f(p_t, S_{t-1}, \mathbb{J}_t; \mu^D)$ if $\mathbb{J}_{jt} = 1$ and 0 otherwise. 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, $dF(c_{t+1}|s, \mathbb{J}_t, c_t, p_t, \chi_t) = dF(c_{t+1}|c_t)$, $dF(\delta_{t+1}|s, \mathbb{J}_t, c_t, p_t, \chi_t) = dF(\delta_{t+1}|\delta_t)$. 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 $\mathbb{J}_t \in \{0, 1\}^F$.[14]

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

been accused of predatory pricing practices. Indeed, the national firm, Monte Paz, sued Philip Morris for predatory pricing due to the pricing at costs we saw in Section 1.2. 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. 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.

[14] Observe that $\mathbb{J}_{jt} = 0$ cannot be interpreted 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.

$$V_f(S_{t-1}, \mathbb{J}_t, c_t, \delta_t) = \max_{p_f, \chi_f} \mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t}\left\{\pi_f(p_\tau, S_{\tau-1}, \mathbb{J}_\tau, c_\tau, \delta_\tau) - \chi_{f\tau}\Theta_f\right\} |\mathbb{X}_t, \Theta_f\right] \tag{1.2}$$

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

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

$$U_f(S_t, \mathbb{J}_t, c_{t+1}, \delta_{t+1}, \Theta_f|\sigma) = -\sigma_f^{\chi}(S_t, \mathbb{J}_t, c_{t+1}, \delta_{t+1}, \Theta_f)\Theta_f + \beta \int V_f(S_t, \beth, c_{t+1}, \delta_{t+1}|\sigma) dP(\beth|\sigma^{\chi}) \tag{1.3}$$

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

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 over Θ_f. The value at this point can be written as

$$\begin{aligned} V_f(S_{t-1}, \mathbb{J}_t, c_t, \delta_t \mid \sigma) &= \pi_f(\sigma^p, S_{t-1}, \mathbb{J}_t, c_t, \delta_t) + \\ &\int \left(\int U_f\left(S_t(\sigma^p), \mathbb{J}_t, c_{t+1}, \delta_{t+1}; \Theta_f \mid \sigma\right) \times dF(c_{t+1} \mid c_t)\, dF(\delta_{t+1} \mid \delta_t) \right) dF_{\Theta_f} \end{aligned} \tag{1.4}$$

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

1.3.2 Optimal choices

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

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

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

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

$$\sigma_f^\phi(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}) = F_\Theta(\bar{\Theta}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \sigma_{-f}^\phi)) \quad \forall f \tag{1.5}$$

Firms' Pricing

Next, observe that, in the single-product case, representing participation choices by the probability of offering product f is without loss of information –in Appendix, A.2.1, we discuss the assumptions to obtain an equivalent representation for multi-product firms.[15] Then, rewriting firm f's problem taking participation probabilities as controls and integrating U_f over realizations of Θ_f we get $U_f = -E\left[\Theta_f \times 1\{\Theta_f \leq \bar{\Theta}(S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1}, \sigma^{\phi}_{-f})\}\right] + \beta E[V(S_t, \gimel, c_{t+1}, \delta_{t+1})|\sigma^{\phi}]$, where the second expectation is taken over all possible choice sets $\gimel$, according to participation probabilities σ^{ϕ} and exogenous distributions. Therefore, in the price-setting stage[16], the Bellman equation of firm f is

$$\begin{aligned} V_f(S_{t-1}, \mathbb{J}_t, c_t, \delta_t|\sigma) = \max_{p_f}\{&\pi_f(p_f, \sigma^p_{-f}, S_{t-1}, \mathbb{J}_t, c_t, \delta_t) - \\ &\int (E\left[\Theta_f \times 1\{\Theta_f \leq \bar{\Theta}(S_t(p_f, \sigma^p_{-f}), \gimel, c_{t+1}, \delta_{t+1}, \sigma^{\phi}_{-f})\}\right] + \\ &\beta E[V(S_t(p_f, \sigma^p_{-f}), \gimel, c_{t+1}, \delta_{t+1})|\sigma^{\phi}] dF(c_{t+1}|c_t)) dF(\delta_{t+1}|\delta_t)\} \end{aligned} \tag{1.6}$$

Taking derivatives of Equation 1.6 with respect to p_f, applying an envelope condition on firms' own entry/exit optimal choices, and noting that $\sum_{\gimel \in \mathcal{J}} \frac{\partial Pr(\gimel|\sigma^{\phi})}{\partial \sigma^{\phi}_r} V_f(\gimel) = E[V_f|\gimel_r = 1] - E[V_f|\gimel_r = 0]$, we get FOC for dynamic prices:

$$\begin{aligned} p_{ft} = &\underbrace{\left(c_f - \frac{\beta}{M}\frac{\partial EV_f}{\partial S_{ft}}\right)}_{\text{Virtual Cost}} - \underbrace{\frac{S_{ft}}{\frac{\partial S_{ft}}{\partial p_{ft}}}}_{\text{Static Markup}} - \underbrace{\sum_{k:\mathbf{J}_{kt}=1, k\neq f} \frac{\frac{\partial S_{kt}}{\partial p_{ft}}}{\frac{\partial S_{ft}}{\partial p_{ft}}}\left(\frac{\beta}{M}\frac{\partial EV_f}{\partial S_k}\right)}_{\text{Dynamic Business Stealing}} \\ &+ \underbrace{\frac{\beta}{M}\sum_{k:\mathbf{J}_{kt}=1}\left(\sum_{r=1, r\neq f}^{F}\left(E[V_f|\gimel_r = 1] - E[V_f|\gimel_r = 0]\right)\frac{\partial \sigma^{\phi}_r}{\partial S_{kt}}\right)\frac{\frac{\partial S_{kt}}{\partial p_{ft}}}{\frac{\partial S_{ft}}{\partial p_{ft}}}}_{\text{Entry Deterrence/Exit Inducing}} \end{aligned} \tag{1.7}$$

[15]Letting $\mathbb{X}' = (S_t, \mathbf{J}_t, c_{t+1}, \delta_{t+1})$, observe that $\sigma^{\chi}_f(\mathbb{X}', \Theta_f) = 1\{\Theta_f \leq \bar{\Theta}_f(\mathbb{X}')\}$, hence $\sigma^{\phi}_f(\mathbb{X}') = \int 1\{x \leq \bar{\Theta}_f(\mathbb{X}')\} dF_{\Theta}(x) = F(\bar{\Theta}_f(\mathbb{X}'))$ and $\bar{\Theta}_f(\mathbb{X}') = F^{-1}_{\Theta}(\sigma^{\phi}_f(\mathbb{X}'))$.

[16]In this section we assume there is only one consumer type, which reduces the states of the game to the market shares by product. This is to obtain expressions that are analogous to the ones we would get in our equilibrium as defined in Section 1.3.3.

Investing and Harvesting The first two terms on the RHS are almost identical to firms' optimal pricing without consumer inertia and would also appear in the case of a monopolist. They indicate that firms mark up some measure of their cost following a rule that depends on the elasticity of demand. However, the key difference is that when there is habit formation, customers become a valuable asset that firms invest in. An additional customer of product j changes firm f discounted expected long-term profits by $\psi_{fj} = \beta \frac{\partial EV_f}{\partial S_{jt}}$. This is the value of an additional customer to the firm. In our model, firms invest in bringing consumers to their products by decreasing prices. Therefore, the additional value of a customer to the long-term profits of the firm enters the price FOC 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*.[17] We can interpret an increase in the incentives to invest in the customer base as a decrease in the virtual cost of serving them. Then, firms mark up virtual costs based on consumers' elasticity. However, note that these markups are a function of the products' locked-in customer base. The more customers a firm has, the more inelastic the residual demand is, and the higher the markup firms want to set. In other words, if a firm has more locked-in customers, it can extract more value from them; that is, it can "harvest" them more. Therefore, the first two terms of Equation 2.13 recast the well-known investing and harvesting incentives (Farrell and Klemperer, 2007) into a FOC that resembles the usual inverse elasticity pricing rule.

Strategic Incentives Third, firms internalize the business stealing effect on all products in the market, even if they do not jointly control them. Firms consider their prices' impact over all other products in the market because they understand that stealing customers from rivals will trigger a competitive response in the future. In principle, this effect can create

[17] 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.

upward or downward pressure on prices. In the multi-product case, firms have two sources of business stealing effects within products in their portfolio. First, the usual static effect. Second, an additional term that considers the long-term losses that sealing customers from other products in its own portfolio generates. 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 firms have *rational* incentives to induce exit or prevent entry in markets with inertia. The relative size of these strategic incentives is an empirical matter.

1.3.3 Equilibrium

This section introduces a framework that facilitates using our dynamic model in empirical applications. First, note that the MPE is not a suitable equilibrium concept in our setting. The payoff relevant variables are past market shares (by consumer type), industry structure, time-varying marginal costs, and mean cigarette valuation. Suppose, for instance, ten relevant products are in the market, and we can summarize the population into four relevant consumer types. Even if we work with a coarse approximation of the value function using ten grid points, the state space would be approximately $11^{(10\times4)}$ plus the size of the exogenous shocks. Neither researchers nor market participants can track this state space for computational reasons.

We aim to construct a tractable equilibrium concept that captures the key strategic interactions between firms. This objective is particularly challenging because, in the game we study, firms' dynamic controls affect the evolution of their own and rivals' states. This property contrasts with "capital accumulation" games, where firms' dynamic controls only affect their own state's evolution. The fact that firms' controls do not affect rival states limits some strategic considerations and simplifies the summary of the industry state by a few aggregates or moments.

Weintraub et al. (2008)' Oblivious Equilibrium (OE) and Ifrach and Weintraub (2017)'s Moment-based Markov Equilibrium (MME) leverage this intuition to construct a computationally feasible approximation of the MPE in capital accumulation games. In the OE case, each firm tracks its own state and assumes rivals are at their stationary level. To the extent that firms do not respond to rivals' positions, this equilibrium concept severely limits the range of strategic responses. On the other hand, in an MME, firms condition their strategies on some summary statistics of their rivals' states. As a result, such relaxation can account for many of the relevant strategic incentives present in the MPE.

However, in the MME, the aggregate moments evolve following a Markov process independent of firms' own strategies. Thus, the straightforward application of this concept to our game would limit some of the strategic interactions potentially present in the MPE of dynamic pricing games such as ours. For instance, while the MME would lead to strategic considerations in the investing-harvesting tradeoff, it would eliminate the dynamic business stealing and entry-deterrence/exit-inducing incentives highlighted in the previous section, which have been shown to impact industry dynamics significantly (Besanko et al., 2010, 2014). In this section, we describe a natural extension of MME, which accounts for firms' influence on the evolution of aggregate market states through their pricing. We refer to this equilibrium concept as Moment-based Markov Equilibrium with Dynamic Spillovers (MME-S). In Appendix Online A.4.6, we show that the stationary outcomes that arise from our equilibrium approximate well those generated by underlying MPE, and improves over those that emerge from the canonical application of the OE and MME.[18]

[18]Although the MPE is computationally infeasible, we can compare the equilibrium outcomes that result in the long run, for whose computation we do not need to solve it, to those generated by alternative equilibrium definitions.

Moment-based Markov Equilibrium with Dynamic Spillovers

Under our approach, firms' best responses depend only on a subset of all the payoff-relevant states, I_f. This subset contains information on the aggregate shares of products in their own portfolio, any other relevant market shares (which might be dominant firms or close competitors), and an aggregate state representing the total sales of all remaining. 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 $\bar{S}^f_{t-1} = \sum_{k \notin T^f} S_{k,t-1}$ the sum of all past shares of non-tracked products. We summarize this information in the firm specific vector $z^f_t = (S^f_{t-1}, \bar{S}^f_{t-1})$. In addition, firms have information about the current choice set, the common component of costs, and mean valuations for cigarettes. Thus, $\xi_t = (\mathbb{J}_t, c_t, \delta_t)$ also belong to I_f. Moment-based strategies are functions from the space information set $\mathcal{I}_f$ to the space of actions (prices and entry/exit decisions): $\tilde{\sigma}_f = \tilde{\sigma}_f(z_t, \xi_t) : \mathcal{I}_f \to [0,1]^{\mathbb{J}_f} \times \mathbb{R}$.

Our main innovation is allowing firms to influence the aggregate state's transition kernels through their dynamic controls. The transition kernel of ξ_t is known and does not require any approximation. On the other hand, firms' f transition kernel of next period market shares, when firm f plays moment-based strategy $\tilde{\sigma}^p_f$ and rivals play $\tilde{\sigma}^p_{-f}$ is defined by

$$S^e(z^f_t, \xi_t; \tilde{\sigma}) = E\left[S(\{S_{ijt-1}\}, \xi_t; \tilde{\sigma}_f, \tilde{\sigma}_{-f}(I_{-f})) | I_f; \tilde{\sigma}\right] \tag{1.8}$$

Even though we are restricting firms' information set to circumvent the curse of dimensionality, firms still internalize the effect of their prices on rivals' next-period shares: they are determined by the derivatives of the *expectation*, $\frac{S^e_{-f}(z^f_t, \xi_t; \tilde{\sigma})}{\partial p_f}$. Note as well that firms take this expectation over both $\{S_{ijt-1}\}$ and I_{-f}, which are unknown from firm f's perspective. To construct this expectation, we follow Fershtman and Pakes (2012) and Ifrach and Weintraub (2017). Concretely, firms draw realizations of last period market shares (the customer base) from the long-run distribution of states over the recurrent class, which we can forward-simulate from any guess of firms' strategies $\tilde{\sigma}$. Naturally, firms can then condition on their information set, which makes some distributions more likely than others. For instance, a firm has perfect information about the shares they track. Moreover, if a firm had 99% of the market share in the last period, particular distributions of rivals' shares are possible. Then, for each realization of market shares, it is easy to construct a corresponding realization of rivals' information set I_{-f} since it implies summing over different groups of market shares. Finally, firms need to evaluate rivals' policies $\tilde{\sigma}_{-f}$ at the corresponding realizations of rivals' information set to construct a realization of rivals' prices $p_{-f}(I_{-f})$. The construction of expected static profits is analogous.

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

$$\tilde{V}_f(I_f|\tilde{\sigma}'_f, \tilde{\sigma}_{-f}) = \pi^{e(f)}(I_f; \tilde{\sigma}_f, \tilde{\sigma}_{-f}) + \beta \int V_f(I'_f|\tilde{\sigma}'_f, \tilde{\sigma}_{-f}) pr(I'_f|I_f, \tilde{\sigma}'_f, \tilde{\sigma}_{-f}) \tag{1.9}$$

Then, we can define our equilibrium concept:

Definition 1 ***MME-S***

The equilibrium consists of

1. *Price and participation policies* $(\tilde{\sigma}^{*p}, \tilde{\sigma}^{*\phi}) : \mathcal{I} \to R^F \times [0,1]^F$

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 2.8 and Equation 2.9.*

Discussion There are a few issues worth noting about our equilibrium definition. First, as in the OE and MME cases, ours is not an equilibrium in the proper sense but rather an approximation of the underlying MPE. The approximation S^e is not necessarily Markov, even if the transition of the underlying variables is. Therefore, firms would be better off conditioning on more information, particularly in longer horizons of the states. 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. In Online Appendix A.4.6, we use forward simulation to show that expected market shares and prices are close to realized outcomes.

Second, observe that summarizing rivals' market shares by summing them is equivalent to assuming that strategic incentives are homogenous across rivals. This assumption is admittedly strong. For instance, a firm might have a more significant incentive to foreclose a competitor closer to its own products in the product space than firms with far-off products. We can accommodate this concern by establishing a more complex information set for firms. However, this would increase the problem's dimensionality and make it harder to solve. The right tradeoff depends on each specific situation.

Existence & Multiplicity In Online Appendix A.5, 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.[19] 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).

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 Online Appendix A.4.3). 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. Online Appendix A.4 describes the algorithm in detail.

[19] 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. 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.

1.4 Estimation

Although we can derive some theoretical regularities from the model, the long-run equilibrium outcomes that result from decreasing habit formation depend on the model's initial primitives. For instance, it is known that lowering consumer inertia can lead to lower or higher prices (Dubé et al., 2009), more or less entry (Farrell and Shapiro, 1988), and ultimately more or less consumption. There are three sets of primitives to recover from data: consumer preferences, marginal costs, and participation costs. We first describe the empirical demand specification and stress the key assumptions. We then move to the supply side. Finally, we summarize the identification and estimation procedure.

1.4.1 Econometric Model

Demand

We construct individual consumption probabilities conditional on past choices and aggregate market shares in the following way.

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,

$$s_{ijtm}(z;\mu^D) = \frac{exp(\bar{u}_{ijtm}(z,\mu^D))}{1 + \sum_k exp(\bar{u}_{iktm}(z,\mu^D))} \tag{1.10}$$

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 $S_{jtm}(\mu^D) = \int s_{ijtm}(z; \mu^D) dF_{tm}(D_i, z)$. If aggregate market share under affiliation z is $S_{jtm}(z, \mu^D) = \int s_{ijtm}(z; \mu^D) dF(D_i|z)$[20], then, taking into consideration that affiliation is a discrete random variable, aggregate market shares can be expressed as $S_{jtm}(w; \mu^D) = \sum_{z \in \{1,\ldots,J\}} w_{tm}(z) S_{jtm}(z; \mu^D) + w_{tm}(0) S_{jtm}(0; \mu^D)$, where $w_{tm}(z) = S_{z,t-1,m}$.

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 stores' 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.

Supply

There are two sources of statistical noise on the supply side: a common knowledge shock to the time-varying marginal costs and an unobserved, private information shock to fixed costs. For the first part, we assume the common marginal costs are taxes plus an unobservable part: $c_{kt} = \theta_k^{vc} + tax_t + \sigma_{\epsilon^c} \epsilon_t^c$, 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, which is distributed $N(0, 1)$. σ_ϵ is a parameter we wish to estimate.

The second source of statistical noise comes from random fixed costs. We assume all

[20] 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.

firms face the same fixed-cost distribution. Its average value decreases with the number of products they sell $\mu^{FC}(N) = \theta_S e^{-\theta_R(N-1)}$, where 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. (θ_S, θ_R) are parameters to recover from data. Finally, we assume the distribution of participation costs is exponentially distributed, simplifying the computation of continuation values and their derivatives.[21] The frequency of the model is annual. We parametrize $\beta = 0.9$ accordingly.

1.4.2 Identification & Estimation Procedure

We estimate the model in three stages. First, we recover the demand parameters. Then, we compute the exogenous variables' transitions directly from the data. Finally, we solve the model to recover the firms' primitives.

Step 1: Consumer Preferences

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 in the product-level data, as in Goolsbee and Petrin (2004).[22]

[21] 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. In our setting, using this assumption, we can express expected fixed costs conditional on offering the product as $E\left[\Theta_k \times 1\{\Theta_k \leq \bar{\Theta}(\mathbb{X}', \sigma^{\phi}_{-k})\}\right] = \sigma^{\phi}_k \times \mu^{FC}_k - (1 - \sigma^{\phi}_k) \times \bar{\Theta}(\mathbb{X}', \sigma^{\phi}_{-k})$

[22] We make two adjustments to the standard procedure. 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 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.

$$
\begin{aligned}
&\min_{\theta} \frac{1}{N} \sum_{i} \sum_{\mathbb{J}_i} 1\{\gimel_i = j\} \times log(s_{ijtm}(\gimel_{i,t-1}; \delta, \theta)) \\
&s.t \quad S_{jtm}(S_{j,t-1,m}, \delta, \eta, \lambda, \gamma) = \hat{S}_{jtm}
\end{aligned}
\tag{1.11}
$$

In the second stage, we decompose mean utility through linear regression,[23]

$$
\delta_{jtm} = \delta_{tm} + \delta_{jm} - \alpha p_{jt} + \Delta\delta_{jtm} \tag{1.12}
$$

Identification Although consumers' choices to smoke or to quit and which product to choose are highly persistent, it could either be due to persistent consumer preferences or structural state dependence (Heckman, 1981). This distinction has crucial implications for firm behavior. In the former case, firms cannot influence their future demand by changing their actions today. Hence, they would not face any dynamic incentive. Therefore, distinguishing between the two scenarios is the key identification challenge in our analysis. Next, we present the sources of variation in our data that help us address this challenge.

Figure 1.3 show that the tax policy has been inconsistent over the years, leading to swings in the tax level.[24] These oscillations are a helpful tool to identify smokers' addiction. The ideal experiment is to observe identical individuals facing the same market conditions (prices, choice sets, etc), choosing with and without dependence on cigarettes. The price swings induced by these tax oscillations provide variation that resembles this ideal experiment. For instance, initial tax increases make smokers more likely to quit smoking –see quitting rates

[23] To make the equilibrium computation tractable, we assume firms disregard the store-specific variation in mean utilities. Thus, we extract the product-specific component of mean utility (δ_j), which does not vary throughout time nor stores, and a time-specific valuation for cigarettes (δ_t), which does not change across stores. So after estimating δ_{tm} and δ_{jm}, we keep the components common to all stores. Aggregating from store-level demand to national demand requires additional adjustments to ensure that the national market shares and elasticity are consistent with the data.

[24] Political swings have made the tax policy inconsistent. Taxes increased from 2005 to 2010 during the presidency of Tabare Vazquez, an oncologist, decreased between 2010 and 2015 after he left office, and rose again in 2015-2020, as he returned to office.

in Table 2.1. 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.

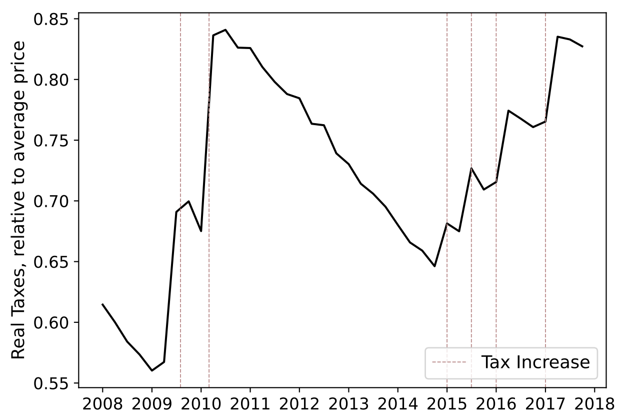


Figure 1.3. Real Taxes.

Then, we exploit substantial variation in the product portfolio and relative prices to identify product loyalty. We observe large shocks to the product portfolio due to the 2009 policy that forced firms to sell only one product under the same brand name. Consequently, several consumers had to make new active choices, which aids in identifying brand loyalty, as in Handel (2013). 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. Note, however, that we cannot identify individual-specific valuations for different products since the policy effectively eliminated products from the choice set.[25] Thus, our strategy uses this moment to determine consumers' persistent preferences for products *characteristics*. Then, any choice persistence that we cannot attribute to these persistent preferences is assigned to brand loyalty. We can also leverage significant relative price swings due to

[25] In that sense, our setting is different from Handel (2013), where 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.

the aggressive reintroduction of products –see Figure 1.1. The intuition on how transitory relative price changes identify brand loyalty is analogous to the price variation we used to identify addiction.

Finally, in the second 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, firms set prices at the national level, 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 fix-effects. Lastly, 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.

Step 2: Exogenous states' transitions.

Then, we use our estimates of δ_t and observed taxes to compute the 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: $tax_t = \mu^{tax} + \rho^{tax} tax_{t-1} + \sigma_{\epsilon^{tax}} \epsilon_t^{tax}$; $\hat{\delta}_t = \mu^{\hat{\delta}} + \rho^{\hat{\delta}} \hat{\delta}_{t-1} + \sigma_{\epsilon^{\hat{\delta}}} \epsilon_t^{\delta}$

Step 3: Firms Costs

After estimating demand primitives and exogenous state transitions, there are $J+3$ remaining parameters: $\theta = \{\theta_k^{vc}, \sigma_{\epsilon^c}, \theta_S, \theta_N\}$. We estimate them using the simulated method of moments (MSM). According to our model, discrete participation decisions are described by the policy $\tilde{\sigma}^{\chi}(z_t^f, \xi_t; \epsilon_t^c, \Theta_{kt}; \theta)$ (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,$\chi_{kt} = \sigma_k^{\chi}(z_t^f, \xi_t; \epsilon_t^c, \Theta_{kt}; \theta_0)$. 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):$p_{kt} = \sigma_k^p(z_t^f, \xi_t; \epsilon_t^c; \theta_0)$. Thus, given the observed data $\{\chi_{kt}, p_{kt}, \{z_t^f\}_f, \xi_t\}_{i=1}^{J\times T}$[26], an MSM estimator of θ_0 can be generated from the conditional expectations: $E[\chi_{kt} - E[\sigma_k^\chi(z_t^f, \xi_t; \epsilon_t^c, \Theta_{kt}; \theta_0)|z_t, \xi_t]|z_t, \xi_t] = 0, E[p_{kt} - E[\sigma_k^p(z_t^f, \xi_t; \epsilon_t^c; \theta_0)|z_t, \xi_t]|z_t, \xi_t] = 0$. Online Appendix A.4.7 shows how to use importance sampling to reduce the computational burden of the estimation procedure.

Moments & Identification Average prices in the data –given estimated levels of inertia and conduct[27]– are informative about marginal costs. Additionally, we leveraged 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 could have used the score of the likelihood of participation decisions as moments in the data. 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. 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. 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.

[26] 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.

[27] Although conduct does not directly identify marginal costs (conditional on prices and demand estimates), it still provides valuable information about the joint distribution of fixed and marginal costs. For instance, a firm that knows a product will likely exit the market will not invest in building a large customer base and increase prices accordingly. 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 A.4.4 presents a graphical illustration of this argument. There, we show 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.

Multiplicity 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 Online Appendix A.5 for details.

Discussion We do not follow any classic approaches to estimating marginal and fixed costs in dynamic models. The standard approach involves inverting static FOC to recover marginal costs and then using those marginal costs to compute static profits, which allows us to recover fixed costs by solving the entry/exit game by maximum likelihood– see for instance (Igami, 2017; Igami and Uetake, 2020; Elliott, 2022). This approach is not feasible because fixed costs influence prices through the choice set probabilities–see Equation 2.13. This issue is not specific to our model but is a general concern for many dynamic pricing games. Similarly, we cannot apply standard solution-free dynamic estimation methods such as Bajari et al. (2007) because we observe a single market (the national market), which is common in many situations. Although we observe substantial variation in observed states, computing policy functions from data alone would be challenging. Lastly, we cannot follow MacKay and Remer (2021) reduce form estimation of dynamic incentives since we do not observe the firms' marginal costs.

1.5 Structural Results & Model Validation

1.5.1 Consumer Preferences

Habit Formation Inertia is high. Smokers are willing to pay almost two times the average price for any cigarette that is not from the brand to which they are loyal and around three times the average 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 2.2 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 A.3.1.

		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		

Table 1.2. Demand Estimates

Elasticity These estimates imply that the mean own-price elasticity in the market is low, around -0.9. It is unlikely that these small elasticities are a product of the identification strategy shortcomings. Low demand elasticity estimates are a robust result among studies treating cigarettes as differentiated products. Ciliberto and Kuminoff (2010); Liu et al. (2015) and more recently Tuchman (2019) obtain estimates in the range of $[-1.35, -0.64]$. Additionally, the implied aggregate market elasticity is slightly below 0.4, which aligns with a large body of work computing smoking elasticities. These figures suggest firms are pricing in the inelastic portion of the demand curve. This pricing behavior is consistent with our dynamic competition model since companies have incentives to constrain the markup they set to retain and capture new consumers from whom they can profit in the future. A static competition model could not capture the observed pricing patterns. We return to this point in Section 1.5.3.

	Own-Price	Agg. Market
Baseline Estimates	-0.853	-0.346
Prev. Literature	[-1.35, -0.64]	[-0.5, -0.15]

Note: Median elasticity in previous literature refers to Ciliberto and Kuminoff (2010); Liu et al. (2015) and Tuchman (2019). Evans and Farrely (1998) reported the aggregate elasticity range.

Table 1.3. Demand Elasticity

1.5.2 Firms' Costs & Pricing Incentives

Firms' Costs Overall, the estimated marginal costs of production (without considering taxes) are small and homogeneous, which aligns with accounting estimates. For all firms, taxes represent more than 90% of marginal costs. 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. Table 1.4 presents the full estimation results.

Pricing Incentives Decomposition: The Role of Strategic Incentives Preferences and cost primitives determine firms' pricing incentives. Table 1.4 shows that virtual costs differ even though production costs and taxes are homogeneous across products. The reason is that consumers from different products have significantly different long-term value for the firm. For instance, locking a consumer in Monte Paz's flagship product is considerably more valuable than making it loyal to a BAT product. Then, we can use our FOC decomposition to gain some understanding of the relevance of strategic incentives. First, we observe that for

	Production Cost	Virtual Cost	Mkp	Static BS	Dynamic BS (Own)	Dynamic BS (Other)	Exit/Entry
MP Flagship	0.0	-0.379	2.819	0.089	0.163	0.128	-0.015
	(0.17)						
MP Regular	0.31	2.128	0.724	0.027	0.922	0.101	-0.009
	(0.05)						
MP Light	0.17	0.655	0.996	0.03	0.859	0.099	-0.01
	(0.07)						
MP Specials	0.0	0.527	0.964	0.028	0.86	0.098	-0.01
	(0.06)						
PM Flagship	0.11	0.674	1.531	0.035	0.04	0.103	-0.001
	(0.09)						
PM Light	0.17	1.15	0.931	0.047	0.147	0.088	-0.001
	(0.13)						
PM Regular	0.02	1.387	0.891	0.039	0.168	0.088	-0.001
	(0.04)						
BAT Standard	-0.01	1.154	0.959	0.016	0.004	0.026	-0.0
	(0.03)						
BAT Premium	0.18	1.803	0.876	0.012	0.022	0.025	-0.0
	(0.17)						
	Other Costs						
$\mu\theta_S$	0.42						
	(0.09)						
$\mu\theta_R$	40.44						
	(44.82)						
$\mu\sigma_\epsilon^2$	0.35						
	(0.34)						

Note: The exogenous process estimates are: $tax_t = 0.243 + 0.860tax_{t-1} + \sigma_{\epsilon^{tax}}\epsilon_t^{tax}$; $\hat{\delta}_t = -0.143 + 0.007\hat{\delta}_{t-1} + \sigma_{\epsilon^{\delta}}\epsilon_t^{\delta}$. These estimates are obtained from linear regression using 44 quarters. Because the persistence of δ_t is quite low, in our baseline estimates and counterfactuals, we assume firms believe $\delta_t = \bar{\delta}_t$, fixed over time. The supply estimates are obtained using importance sampling. The coefficients reported the mean of the obtained distributions. The variance estimates are the following: $\sigma_{mc}^2 = 0,0351, \sigma_{\theta_S}^2 = 0.041, \sigma_{\theta_R}^2 = 110.35, \sigma_\epsilon^2 = 0.026$. Standard errors are computed using standard formulas from MSM. We decompose prices using the multi-product version of the first-order conditions of the model presented in Section 1.3. We evaluate the different terms of the decomposition at the observed states of the industry and average them for every product. These are preliminary results.

Table 1.4. Cost Estimates, Exogenous Process, and Price Decomposition

relatively more minor products within a firm's portfolio (for instance, Monte Paz' Specials and Regular or Philip Morris Regular), dynamic business stealing effects with respect to other products within their portfolio are substantially more important than the static ones. This means that firms have less incentive to expand smaller product lines once we consider the dynamic implications than in a static model.

Finally, our estimated primitives suggest that firms lack significant incentives to induce rivals' exit or deter entry. While our model introduces rational incentives to predate, the existing asymmetry among firms indicates that ousting rivals from the market is either exceedingly challenging or not lucrative. On the contrary, firms appear more inclined towards softening competition to avoid potential reprisals that could spark fiercer competition in subsequent periods. Indeed, we observe that the dynamic business stealing effects with respect to products of other firms are almost as important as the static business stealing effects–and in some cases even more important, for instance, the case of BAT products. This implies that firms set prices higher than they would otherwise to avoid stealing consumers from rivals. 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.[28]

1.5.3 Model Validation - Firm Behavior under Habit Formation

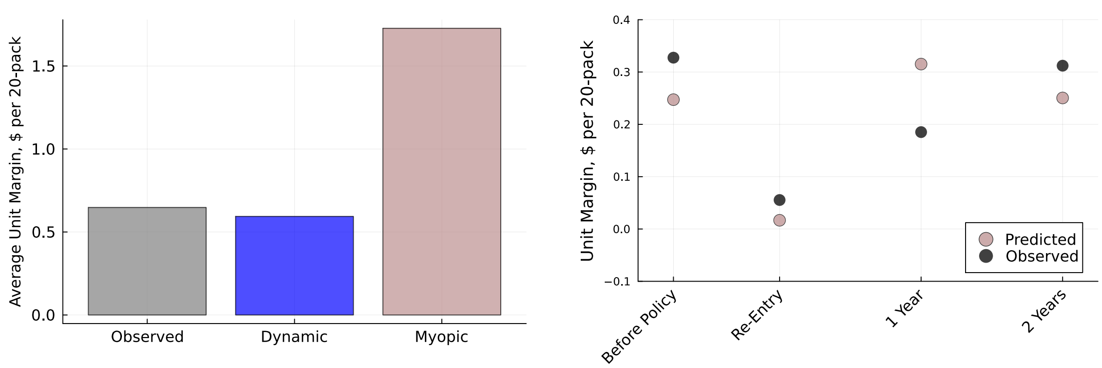
Before using the structural estimates to evaluate the effect of nicotine caps and uniform packaging, we provide empirical evidence that firms' pricing strategies are consistent with forward-looking behavior under the estimated addiction and brand loyalty levels. We highlight two features that allow us to validate our assumptions. First, the model rationalizes 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 used to introduce new products, observed in the data and discussed in Section 1.2.

Low Markups Despite Inelastic Demand First, we show that observed elasticity is consistent with firms' forward-looking behavior. We take the estimated consumer primitives

[28] 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. 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.

but assume that all costs firms face are taxes. Then, we solve the model both for forward-looking and myopic firms. Moreover, we solve the equilibrium for all possible choice sets, assuming products would remain in the choice set indeterminately in every case. These assumptions make our results independent of any supply estimate.

Then, we compare the unit margins in each case. The unit margins that myopic firms would set are approximately three times larger than those observed and those set by forward-looking firms. This result is consistent with forward-looking firms keeping prices relatively low despite consumers' unresponsiveness because of the long-term profits these consumers can generate. For firms, high incentives to invest in consumers are equivalent to low virtual costs, compensating for the higher incentives to charge consumers more. In other words, consumers' state dependence explains why the equilibrium elasticity remains low: firms internalize the long-term profits, not just the short-term gains. The fact that we assume all costs firms face are taxes makes this result even more striking since it implies that we would need significant negative marginal production costs to rationalize a static competition model.



(a) Price Comparison, Static v. Dynamic (b) 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.

Figure 1.4. Model Validation - Firm Behavior under Habit Formation

Introductory Pricing: Investing in Consumers Next, we argue that firms' strategies to introduce new products are consistent with our conduct model. More generally, this means that firms' price responses to changes in the size of their loyal customer base are consistent with our competition model at the estimated consumer inertia. Figure 1.4b compares Philip Morris's aggressive introductory pricing strategy with the model's prediction. The model predicts a sharp margin drop consistent with Philip Morris's pricing around marginal cost. If persistent choices were due to persistent preferences, firms would not have incentives to modify prices as a response to changes in the customer base. Our model captures their response to the loyal customer base, which suggests that firms' beliefs about habit formation are not too different from our estimates.

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, persistent choices are due to persistent preferences, or myopic firms 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. Finally, Table 1.5 shows that under the estimated primitives, the long-run steady state of the economy fits shares, prices, concentration ratios, switching patterns, and elasticity very well.

1.6 Reducing Habit Formation in Tobacco Markets: Nicotine Caps and Uniform Packaging Policies

In this section, we use our estimates to analyze the effect of two policies: capping nicotine content and standardizing the packaging of tobacco products. We focus on these policies for two reasons. First, while they are currently under discussion in the United States and

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. This column's tax process is fixed at $1.85.

Table 1.5. Comparison of Actual and Simulated Moments

other countries, there is little empirical evidence to evaluate their impact. Second, they are salient examples of policies that would reduce the degree of habit formation in tobacco consumption by lowering addiction and consumers' loyalty to particular products. Nonetheless, our framework is more general and can be used to study various policies such as taxation, increasing the lump sum costs of offering new products, and competition policy. We evaluate the impact of the FDA's nicotine caps by reducing the estimated "addiction" parameter and analyze uniform packaging by lowering both the mean cigarette valuation and consumer loyalty. We solve equilibrium policies for each counterfactual demand parametrization and simulate the industry 2,500 times. All the results we present in this section are the average over the long-term stationary distribution of states when taxes are equal to $1.85 per pack of 20 cigarettes.

1.6.1 Nicotine Caps

In 2018, the FDA issued an advanced notice of public rulemaking to establish a maximum nicotine level in cigarettes–and potentially other tobacco products–to minimally or non-addictive levels.[29] Nicotine is the main addictive chemical in cigarettes and is responsible for the habit-forming properties of tobacco. The FDA's goal is to reduce the addiction potential of cigarettes and, consequently, help addicted smokers quit and limit the amount of new smokers becoming regular users. Results from clinical trials suggest that reducing nicotine to approximately 0.4 mg or less per gram of tobacco allows consumers to quit smoking at higher rates without compensatory effects. Our results isolate the equilibrium impact of reducing addiction from other potential changes in consumer preferences. This analysis complements previous results by providing a framework to understand how firms would respond when selling a less addictive product.

Holding firms' strategies fixed, if nicotine caps eradicate tobacco dependence (i.e., we shift the addiction parameter to 0.0), the Uruguayan smoking rate would decrease 33.4% to slightly below 13.5% of the population. When firms adjust their strategies, they reinforce the effect, reducing the smoking rate up to 20% more, as shown in Table 1.6.[30] Although average prices decrease around 8.2% because of the policy, they are 4.8% higher than if firms did not adjust their strategies. Moreover, the number of products in the market decreases slightly. Overall, such price and portfolio re-optimization allow firms to increase their average profits by 9.0%

To illustrate the role of supply responses, we show how firms' optimal prices change as we eliminate addiction and how that impacts long-run consumption. Figure 1.5 depicts these changes for the case of the national firm's flagship product–the intuition holds for any product in the market. The solid black curve indicates the optimal pricing function when addiction is at the baseline level. It determines the average optimal price for each size of

[29]This proposal is both technically and legally feasible under the 2009 Family Smoking Prevention and Tobacco Control Act (TCA) (Berman et al., 2018)

[30]These results are consistent with simulation exercises carried out in the US and New Zealand, which found reducing nicotine to non-addictive levels would lower cigarette smoking rates between 40% and 80% (Laugesen and Grace, 2015; Apelberg et al., 2018). Although we can use these studies as a benchmark, they rely heavily on expert elicitation of crucial parameters.

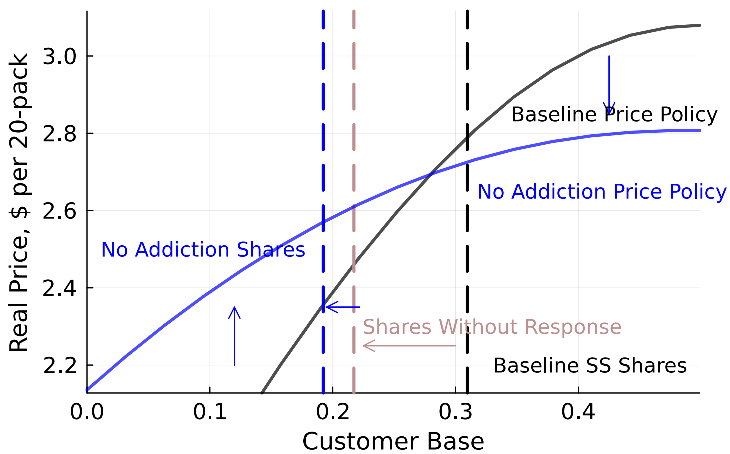
	Baseline	No Addiction/Baseline Strategies	No Addiction/Equilibrium
Smoking Population (%)	20.2	13.45	10.99
Average Price	2.57	2.25	2.36
Product Lines	6.12	6.08	5.77
Profits	355.38	134.36	146.46

Note: For each scenario, we take demand and supply primitives, solve equilibrium policies according to the definition in Section A.4.2, and simulate the industry for 150 periods 2,500. The outcomes reported in this table are the average over the visited states in the long-run station distribution (after burning the first 100 periods). In Figure A.3.3, we present the distribution of one key summary statistic of the states: aggregate consumption. In the "Baseline" scenario, the addiction parameter (η_0) is 2.007, and the brand loyalty (η_1) is 3.437. For the "No Addiction/Baseline Strategies", we set parameters $\eta_0 = 0.0$, $\eta_1 = 2.437$, but the economy is forward-simulated using the equilibrium policies at the baseline addiction level. We fix costs at \$1.85 per 20-cigarette pack in all scenarios. We compute the average smoking rates assuming that the available market size represents 35.6 % of the population, which was the average smoking rate in Uruguay in 2000. Figure A.3.4 shows average consumption, prices, and number of products for several intermediate values of the addiction parameter, with and without firm responses.

Table 1.6. Equilibrium outcomes under nicotine caps.

its own customer base. The optimal pricing function is a steep function of the customer base: Under current levels of addiction, firms are willing to offer a low price to attract new customers when not many individuals consume their product. As the customer base grows, the firm increases its price to exploit the –partially– locked-in customers.

The direct effect of eliminating addiction is to reduce *smokers*' valuation for cigarettes. So, if firms do not adjust their strategies, the demand for cigarettes drops, and the average long-run consumption decreases as well. If firms do not internalize the new addictiveness scenario, they would significantly lower prices to partially recover their lost customers– consumption drops despite prices decreasing from 2.8 to 2.45. However, once firms internalize that cigarettes are no longer addictive, this is not their optimal response. Firms recognize that they cannot retain customers and profit from them in the future as efficiently as before. Therefore, consumers' long-term value to the firm decreases. This, in turn, discourages firms from lowering prices to attract consumers to the market–a decrease in the long-term value of consumers is equivalent to increasing the virtual cost of serving them. Thus, the optimal pricing function shifts up even though the aggregate cigarette demand decreases. Therefore, we observe a price increase over the relevant customer base range, which further drops consumption and rationalizes why firms tend to reinforce the policy's direct effect.



Note: The solid curves (black and blue) represent Monte Paz's optimal pricing function for its flagship product. It establishes the firm's average price for each size of its customer base, that is, the average across all possible prices optimally set depending on rivals' customer bases and the number of smokers. The black policy is calculated when the addiction parameter is $\eta_0 = 2.007$, and the brand loyalty at $\eta_1 = 3.437$. The blue line represents the case where $\eta_0 = 0.0$, $\eta_1 = 2.437$. We fix costs at \$1.85 per 20-cigarette pack in all scenarios. The dashed lines represent the average market share of the product in the long-run stationary distribution, obtained by simulating the economy 2,5000 times. Because these are the average shares, they also represent the average customer base of the product, that is, how many consumers, on average, were consuming the product in the previous period. The black line is the average market share of Monte Paz's flagship product under the baseline scenario. The pink vertical dashed line represents the average customer base when addiction is $\eta_0 = 0.0$ eliminated, but firms continue to play the strategies at the baseline addiction level (blue policies). The blue vertical line represents average market shares when addiction is $\eta_0 = 0.0$, and firms play their optimal strategies according to this scenario. The intersection between the solid black line and the vertical dashed line represents Monte Paz's flagship product's average prices and market shares across the stationary distribution of states in the long run. The intersection between the black policy and the vertical pink line represents prices and shares when the firms play the baseline strategies, but addiction is set at $\eta_0 = 0.0$. Finally, the intersection between the blue policy and the blue vertical dashed line is the prices and quantities the product sells under the equilibrium without addiction.

Figure 1.5. Price Policy - Monte Paz, Flagship, Addiction

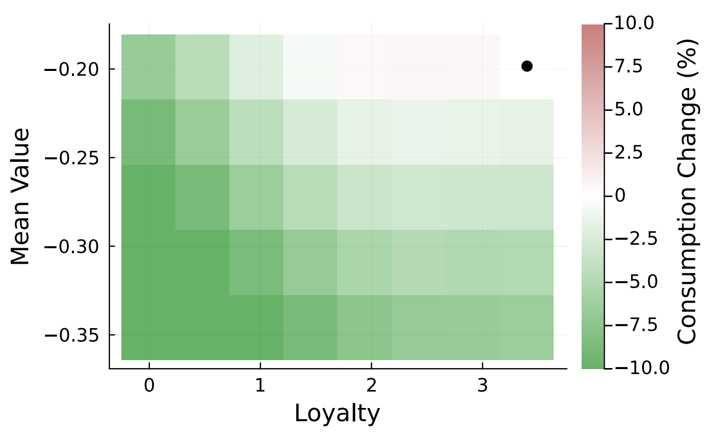
Robustness The FDA recognizes that nicotine caps could have unintended consequences beyond making cigarettes non-addictive (FDA, 2018). In particular, there is concern that consumers could increase their cigarette consumption to maintain their nicotine intake. Our model did not explicitly characterize the relationship between cigarette consumption, addiction, and nicotine content. Although we have access to nicotine content and could model demand for nicotine explicitly, the range of variation in nicotine content is outside what the medical literature considers necessary to eliminate the addictive properties of tobacco. While recent clinical trials suggest that moderate reductions in nicotine content could lead to increased smoking intensity and more significant exposure to harmful chemicals, they observe that sufficiently large reductions encourage consumers to quit smoking without compensatory effects (Berman and Glasser, 2019). Thus, according to these studies, extrapolating compensatory behaviors from a demand model estimated with limited variation in nicotine–particularly within the addictive range—would be inappropriate to evaluate the effect of limiting nicotine to non or minimally addictive levels.

1.6.2 Uniform Packaging: Industry Lobby and Economic Considerations

Australia became the first country to implement uniform packaging for tobacco products in 2012. The policy forced firms to sell all their products in standardized packages with no branding or logos – Figure A.1.4 illustrates how packages should look. The policy aims to reduce the appeal of tobacco products, particularly to young people, and to enhance the effectiveness of health warnings. The tobacco industry has opposed this policy, arguing that it would reduce brand loyalty, causing smokers to switch to cheaper brands and encouraging price competition between manufacturers (Chantler, 2014). Since 2017, many countries have adopted similar policies, including the UK, France, and New Zealand. However, the empirical evidence on the effectiveness of this policy is scarce and usually confounded with the effect of other measures implemented simultaneously. Our counterfactual analysis allows us to isolate the potential impact of uniform packaging on tobacco consumption. To consider policymakers and industry arguments, we evaluate the effects of this policy by reducing both the mean valuation for cigarettes and consumers' loyalty.

Price Responses

If firms adjust their prices but keep portfolio strategies fixed, uniform packaging would reduce consumption in most scenarios we analyze. Figure 1.6 shows the percentage change in long-term average consumption for several levels of brand loyalty and mean valuations (we assume that reducing brand loyalty does not increase quitting at observed prices but only increases switching between products). Contrary to industry claims, we show that even if the effect of the policy does not reduce consumers' appeal for cigarettes, the policy can have significantly favorable effects. If the uniform packaging eliminates brand loyalty, but cigarettes' valuation does not change, consumption would still decrease by approximately 6.8%. In the worst case scenario, when loyalty decreases around 30%, the average smoking rate in the country increases at most 0.68%. If the policy achieves a decline in the valuation of cigarettes of at least 15%, then the policy would reduce consumption no matter how much brand loyalty declines.



Note: Note: For each counterfactual scenario, we take demand and supply primitives, solve equilibrium policies according to the definition in Section A.4.2, and simulate the industry for 150 periods 2,500. This figure compares and reports the percentage change in average consumption over the visited states in the long-run station distribution (after burning the first 100 periods). All comparisons are in relation to the baseline scenario where the addiction parameter is $\eta_0 = 2.007$, and the brand loyalty is $\eta_1 = 3.437$, which is represented in the top-right corner by a black dot. We fix costs at \$1.85 per 20-cigarette pack in all scenarios. Green colors indicate that consumption decreases from our average consumption in our baseline scenario, while red indicates that consumption increases.

Figure 1.6. Percentage change in long-term average consumption under uniform packaging.

Even though our results contradict the tobacco industry's claims, their arguments are sensible. According to our findings, uniform packaging would make consumers significantly more price-sensitive and lead to more frequent product switching. Indeed, in the worst-case scenario from a policy point of view, i.e., when cigarette valuation is not affected, the average price elasticity increases up to 2.5 times, and the average probability that a consumer repeats its product choice over time decreases by a factor of 3.5. Table 1.7 shows these figures. In static models, such an increase in demand elasticity would lead to substantial price drops and consumption increases, which is at the core of tobacco companies' opposition to uniform packaging. Indeed, we show that if firms were myopic, prices would decline approximately 15% –see Figure A.3.5f. However, we have provided robust evidence that firms also consider the long-term implications of their pricing decisions. Indeed, firms' change in dynamic incentives as we lower consumer loyalty reconciles this paradoxical result of lower consumption under more elastic demand.

A decline in brand loyalty has two main effects on firms' optimal pricing strategies, which we illustrate in Figure 1.7 taking the national firm flagship product as an example. First, as consumers become more price-sensitive, firms' markups decrease and become less sensitive to the size of the customer base. This effect alone would substantially lower prices, particularly for firms with a large equilibrium customer base (clockwise rotation), as shown in Figure 1.7a. However, eliminating brand loyalty decreases the long-term value of an additional customer to the firm. This value decreases because consumers are significantly more likely to switch to other products in the future. As a result, virtual costs rise as brand loyalty falls. The increase in virtual costs, in turn, shifts up the policy, i.e., the prices firms charge for any level of their customer base. The joint effect of virtual costs and static markups is to rotate the price policy clockwise and shift it up. According to our estimates, the long-run average virtual cost increases by a factor of four when we eliminate brand loyalty– see Table 1.7. The offsetting effect of decreasing markups and raising virtual costs leads to a small, non-

		No Loyalty		75% Loyalty	
	Baseline	Fixed Portfolios	Equilibirum	Fixed Portfolios	Equilibirum
Consumer Behavior					
Smoking Population (%)	20.37	17.11	18.29	20.46	20.95
Elasticity	-1.56	-3.55	-3.55	-2.47	-2.47
Prob. Repeating	0.82	0.24	0.23	0.63	0.64
Price Decomposition					
Price	2.59	2.53	2.54	2.55	2.55
Virtual Costs	0.26	1.08	1.08	0.65	0.65
Markups	1.9	0.76	0.76	1.25	1.25
Profits	368.29	307.18	308.79	361.45	360.24
Portfolio Decisions					
Product Lines	6.3	6.49	7.54	6.44	7.0
HHI	6009.58	5839.82	5635.3	6108.36	6108.26
Endog. Entry Cost	0.09	0.05	0.05	0.08	0.08

Note: For each scenario, we take demand and supply primitives, solve equilibrium policies according to the definition in Section A.4.2, and simulate the industry for 150 periods 2,500. The outcomes reported in this table are the average over the visited states in the long-run station distribution (after burning the first 100 periods). In Figure A.3.3, we present the distribution of one key summary statistic of the states: aggregate consumption. In the "Baseline" scenario, the addiction parameter (η_0) is 2.007, and the brand loyalty (η_1) is 3.437. For the "No Loyalty" scenarios, we set parameter $\eta_1 = 0.0$, and for the "75% Loyalty" is $\eta_1 = 2.43$. In the "Fixed Portfolios" columns, the industry is simulated using firms' equilibrium portfolio strategies computed under the "Baseline" parametrization. In the columns under "Equilibrium", both price and portfolio equilibrium policies correspond to the parameters indicated in each column. In all cases, mean valuation is at its baseline level $\delta_t = -0.1468$. We fix costs at $1.85 per 20-cigarette pack in all scenarios. We compute the average smoking rates assuming that the available market size represents 35.6 % of the population, which was the average smoking rate in Uruguay in 2000. Figure A.3.5 shows consumption, elasticity, switching behavior, prices, virtual costs, and markups for intermediate levels of brand loyalty.

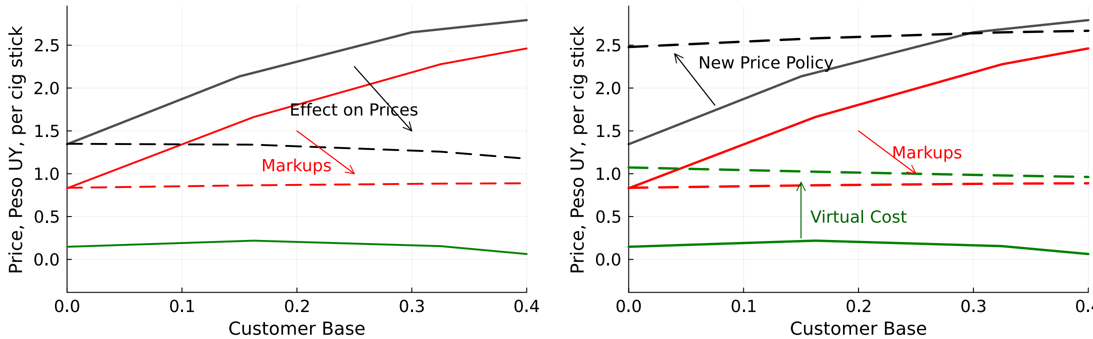
Table 1.7. Equilibrium outcomes under uniform packaging (no change in mean utility).

monotonic effect on prices and reconciles the possibility of large increases in demand elasticity with drops in consumption.[31]

Portfolio Adjustments

Next, we evaluate how portfolio adjustments influence uniform packaging's overall impact. Figure 1.8 compares its effect on long-term consumption when firms keep their portfolio de-

[31] 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. In this case, 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, the market leader loses its dominant position, and the investing incentives dominate. This pattern is consistent with several recent papers exploring the relationship between prices and switching costs (Dubé et al., 2009; Arie and E. Grieco, 2014; Fabra and García, 2015; Cabral, 2016).



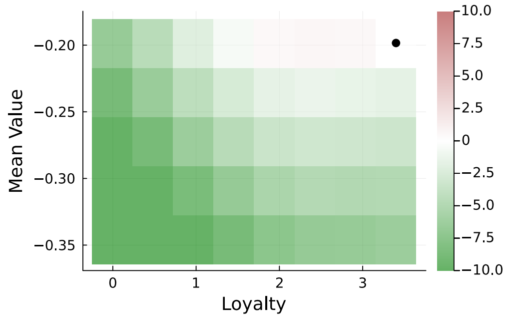
(a) Effect on Static Markups (b) Effect on Virtual Costs

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 using 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. illustrates the effect of eliminating brand loyalty from the baseline estimates (holding mean valuations fixed) for the national firm's flagship product

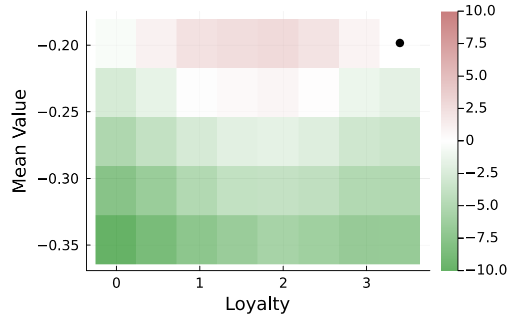
Figure 1.7. Price Decomposition - Monte Paz, Flagship

cisions fixed and when they optimally adjust them. We find that portfolio adjustments have a significant impact on consumption. Specifically, the expected number of available products increases as brand loyalty drops. If uniform packaging eliminates loyalty without affecting cigarette valuation, firms will offer, on average, 7.5 product lines, which is significantly larger than the 6.5 product lines we observe in the baseline scenario. Thus, for intermediate levels of brand loyalty, which coincide with the most significant decrease in prices, consumption might increase up to 2.9%. Furthermore, in this case, the mean valuation for cigarettes needs to drop around 35% to ensure consumption decreases for any level of brand loyalty.

Two factors establish the negative correlation between brand loyalty and the number of available products. First, demand becomes more symmetric as loyalty declines. If we assume all products were offered in the market, eliminating brand loyalty would decrease the HHI by around 650 points –see Table 1.7. Thus, relatively disadvantaged products can generate more profits at the expense of the market leaders. Because the existing market structure is very asymmetric, the "losses" the market leader faces as loyalty declines are enough to subsidize the entry of multiple smaller products, which can reach a sustainable



(a) Fixed Participation Policies



(b) Full Equilibrium

Note: Note: For each counterfactual scenario, we take demand and supply primitives, solve equilibrium policies according to the definition in Section A.4.2, and simulate the industry for 150 periods 2,500. This figure compares and reports the percentage change in average consumption over the visited states in the long-run station distribution (after burning the first 100 periods). All comparisons are in relation to the baseline scenario where the addiction parameter is $\eta_0 = 2.007$, and the brand loyalty is $\eta_1 = 3.437$, which is represented in the top-right corner by a black dot. We fix costs at \$1.85 per 20-cigarette pack in all scenarios. Green colors indicate that consumption decreases from our average consumption in our baseline scenario, while red indicates that consumption increases.

Figure 1.8. Percentage change in long-term average consumption under uniform packaging.

customer base. Therefore, the market sustains multiple new, small product lines without sacrificing the presence of the established products. Second, the endogenous entry costs decline. We define endogenous entry costs as the initial investment necessary to gain a sustainable customer base. We measure it by computing the difference between a product's value when it has no loyal customer base versus its value at its steady-state level. The gap between initial and steady-state values goes from around 10% in our baseline scenario to 5% when there is no brand loyalty. In other words, firms are more willing to introduce new products when they can free-ride on their rivals' efforts to attract customers.

Overall, our results show that uniform packaging can positively affect cigarette consumption but can also backfire. On the one hand, it decreases the value of customers for firms, discouraging them from attracting new consumers. On the other hand, it might facilitate the introduction of new varieties as demand becomes more symmetric and endogenous entry costs decrease. These results are consistent with a handful of studies that analyze the effects of uniform packaging after its implementation. Although the evidence is anecdotal mainly and the analysis descriptive, they have found a small impact on prices and a more significant increase in the number of available varieties, without a significant effect on aggregate consumption (Breton et al., 2018; Underwood et al., 2020; Moodie et al., 2022).

Robustness Uniform packaging could also reduce product differentiation beyond its effect on brand loyalty. If that were the case, the policy would induce more price competition without discouraging firms from attracting new consumers. Although it could still prevent them from investing in new consumers by decreasing industry profits, it would not do so directly through the probability of retaining customers. Hence, in this case, the investing incentives would not decrease as much, potentially leading to more price competition and a more significant increase in consumption. In Figure A.3.6, we show that if uniform packaging eliminates all vertical differentiation between products without affecting brand loyalty, consumption might increase up to 8%.

1.7 Conclusions

The theoretical literature posits that firms are strategically motivated to adapt their pricing and product strategies to foster consumers' habit formation and maximize long-term profitability. Our empirical findings strongly support these theories, demonstrating that firms indeed adjust their behavior to exploit consumer inertia. Moreover, we show that relatively simple adjustments to the traditional workhorse models in economics are sufficient to take these models to the data, which allows us to understand better the effect of policies in markets with habit formation. In particular, in the case of sin goods, we stress that policymakers should leverage these incentives to design policies that discourage consumption through companies' responses. This strategy has the advantage of decreasing their use without shifting the burden to consumers as much.

Chapter 2

Dynamic Equilibrium Effects of Sin Taxes for Addictive Products

2.1 Introduction

Governments frequently seek to curb the consumption of sin goods like tobacco, alcohol, and sugary drinks by imposing taxes on them. Two features characterize these industries. First, these markets are usually imperfectly competitive–and sometimes highly concentrated. Second, consumers typically exhibit some degree of addiction to these goods, the tobacco case being the most paradigmatic. Although the public economics literature has studied the optimal taxation of sin goods, it has largely overlooked the implications of these two characteristics. In this paper, I leverage industrial organization tools to study the optimal taxation of addictive goods in imperfectly competitive markets.

Recent studies have shown that the pass-through is a crucial sufficient statistic to determine the welfare implications of taxes both in perfect and imperfectly competitive markets (Weyl and Fabinger, 2013). In oligopoly markets, two factors determine firms' pass-through: the curvature of demand and firms' conduct.[1] The addictive nature of sin goods impacts these two dimensions. Consumers of these goods experience tolerance, reinforcement, and withdrawal effects (Becker and Murphy, 1988). Therefore, current purchases are a function of past consumption, and the intensive margin of consumption becomes a relevant dimen-

[1] See Miravete et al. (2023) for an excellent discussion.

sion. This intensive margin, in turn, has important implications for the demand curvature (Anderson et al., 1992). Moreover, the intertemporal link of demand induces firms to consider the long-term implications of their pricing decisions. For instance, Klemperer (1987a) found that consumer inertia encourages firms to lower prices to attract a larger customer base (invest) and then raise them to profit from the locked-in consumers (harvest).

In this paper, I show that flexibly modeling the specific dynamic elements of demand and supply for addictive goods in imperfectly competitive markets has essential implications for pass-through. I then identify and estimate the model using data from the Uruguayan cigarette industry. I show that such a dynamic model is needed to capture the observed elasticity and pass-through. Finally, I use this framework to design tobacco taxes and evaluate their welfare implications.

In Section A.1, I show that the cigarette industry presents some features that distinguish it from most differentiated product markets. First, I stress that consumers' addiction to cigarettes makes consumption choices extremely persistent and introduces heterogeneity in the intensive margin of consumption. Second, I highlight that demand elasticity is significantly lower than in most markets, with firms usually pricing in the inelastic region of the demand curve. I also present some evidence that elasticities are insensitive or even increasing with prices, suggesting that demand is "more" long-convex than in most industries. Finally, I exhibit that firms tend to over-shift taxes, often passing more than 200% of the tax, even though there is considerable heterogeneity across firms, products, and tax change events.

I develop a model of demand and supply for cigarettes that captures these features. Consumers have an individual-specific stock of addiction that depends on the intensity of past consumption and determines both the possibility of smoking and the number of cigarettes consumed. I show that the introduction of this intensive margin, due to past consumption, modifies the curvature of demand with respect to traditional discrete choice models, such as the logit. In particular, it allows the reach curvatures closer to the super-convex region defined by the CES model. The intuition is straightforward: quitting additional cigarettes becomes increasingly harder, particularly for heavily dependent consumers. Thus, demand becomes more inelastic as prices increase.

On the supply side, firms are forward-looking and price their products to maximize long-term profits. To alleviate the computational challenges, I assume firms only partially account for rivals' strategic responses and use an Oblivious Equilibrium as the equilibrium notion (Weintraub et al., 2008).[2] Firms' internalization of the dynamic incentives introduced by addictive goods modifies the relationship between the curvature of demand and the pass-through of taxes established for imperfectly competitive markets in static settings. While firms continue to consider how elasticities change as they increase prices, they now consider how their incentives to "invest" in bringing new consumers to the market evolve at higher price levels. We show that just as the tradeoff between investing and harvesting determines equilibrium prices, the change in the incentives to invest and harvest governs the pass-through of taxes.

I leverage consumers' and firms' actions to connect the model with the data. On the consumer side, I combine product-level data and a panel of smokers with rich variation from the Uruguayan experience. First, I show that the correlation between the number of cigarettes consumed, income, prices, and individuals' stock of addiction identifies the Box-Cox parameter. Then, I use significant tax oscillations and a policy that forced approximately 40% of products out of the market to determine the effect of habit formation on the extensive consumption margin as in Pareschi and Lopez (2024). Next, I build on MacKay and Remer (2021) approach and show that firms' FOC and pass-through equations identify firms' value function first and second derivatives at observed states. These elements are sufficient to obtain a linear characterization of the first derivative of the value function outside the

[2]Pareschi and Lopez (2024) discuss how such equilibrium notion differs from the underlying Markov Perfect Equilibrium and other potential relaxations.

observed states, which is enough to carry out counterfactuals.

The structural estimates suggest that the demand is closer to the CES model than the logit, which is in line with our descriptive evidence. This result implies that consumers find it harder to make additional cuts in consumption as prices increase. On the supply side, we find that the change in the incentives to invest in new consumers explains the significant heterogeneity in the observed pass-through and simultaneously allows rationalizing high over-shifting with low curvatures and under-shifting with high ones.

Literature Review This paper makes policy, economics, and methodological contributions. First, we contribute to the recent literature on sin tax design in imperfectly competitive markets. For instance, Miravete et al. (2018) and Hollenbeck and Uetake (2021) study how the Laffer curve changes once we account for market power in the alcohol and marihuana industries respectively, Conlon and Gortmaker (2020) observe that over-shifting of alcohol taxes can be due to nominal rounding. Like this paper, Abi-Rafeh et al. (2023) and Wang (2015) analyze firms' dynamic incentives to study the impact of taxes in the sugar-sweetened beverage industry. I contribute to this literature by stressing how the addictive nature of sin goods modifies policy incidence and optimal taxes.

From an economic point of view, this paper contributes to the literature by studying the relationship between the shape of demand and pass-through in oligopoly markets. (Anderson et al., 1992) first showed that a representative consumer could rationalize the CES aggregate demand function within a discrete-continuous choice model. More recently, Griffith et al. (2018), Birchall and Verboven (2022) and Miravete et al. (2023) have noted that the introduction of either flexibility in the heterogeneity of consumers' price sensitivity of non-linear income effects are required to flexible the curvature restriction imposed by traditional discrete choice models such as the logit. Furthermore, Weyl and Fabinger (2013) derives pass-through formulas for several competitive environments and determines its relationship with demand curvature in each case. I show how the demand and supply dynamic incentives introduced by addiction modify these relationships.

Finally, from a methodological point of view, this paper contributes to the literature on empirical dynamic oligopoly models. In particular, I note that pass-through regressions can help identify the shape of the derivative value function, building on the approach developed by MacKay and Remer (2021), which estimates dynamic incentives from markup equations. This approach has also been recently used by Dubois and Pakes (2024) to study the effects of advertising in the pharmaceutical industry.

2.2 Descriptive Evidence

2.2.1 Data

We use two primary 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. The market structure is simple. Three players participate in the Uruguayan cigarettes market.[3] 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

[3] Observe that we are excluding three potentially relevant substitute products. First, we exclude roll-your-own tobacco products. Second, we are also omitting the smuggled cigarette products. Finally, note that our sample period coincides with the rise of e-cigarette sales in the US (Tuchman, 2019). However, Uruguay forbade the commercialization of e-cigarettes. 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.

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.

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. Initially, the panel included only smokers, but if they decided to quit between interviews, they stayed in the sample. This panel contains information about 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. 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. Appendix A.1 summarizes this information and presents the details of the product aggregation.

2.2.2 Consumer Preferences: Addiction & Intensive Margin of Consumption

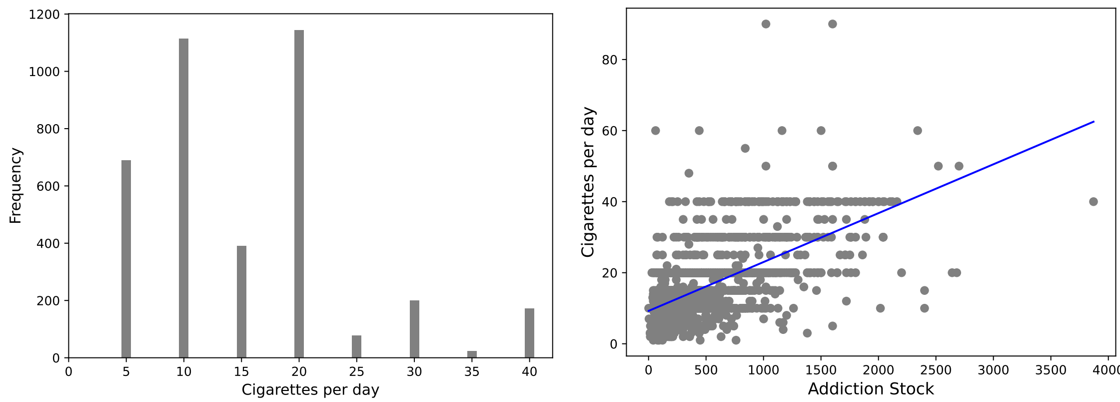
Relative to other industries, what characterizes the cigarette market is that consumers are addicted to tobacco. Becker and Murphy (1988) observed that consumption patterns exhibit reinforcement and tolerance. These two features make consumers more likely to consume cigarettes if they have consumed them in the past. It also stresses the importance of accounting for the intensive margin of consumption since individuals' "stock of addiction" modifies how much consumption is valued today. Table 2.1 shows that the overall quitting rate over two years is between 15% and 25%, and the relapsing rate is around 21%. Additionally, consumers tend to repeat the same product choices they did in the past. On average, two-thirds of smokers repeat their choice every two years.

		Repeat Choice	Smoke
Smoker Status	Year		
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

Note: This should be considered the probability of repeating a choice every two years.

Table 2.1. Switching matrix for smokers and non-smokers

Moreover, we observe substantial heterogeneity in the number of cigarettes smokers consume. Figure 2.1a shows the distribution of cigarettes consumed by smokers in the sample. The distribution is highly skewed, with a substantial mass of consumers smoking between 10 and 20 cigarettes per day. Figure 2.1 emphasizes that the number of cigarettes consumed "today" strongly depends on the number of cigarettes consumed in the past and the years the consumer has been smoking. In Table B.1.1, however, I show that the intensity of past consumption is not a relevant determinant of the probability of quitting altogether, i.e., of the extensive margin. Similarly, which product the consumer is smoking today is not a relevant determinant of the likelihood of quitting nor the number of cigarettes smoked.



(a) Cigarettes per Day, Distribution (b) Quantity Smoked by Stock of Addiction

Figure 2.1. Consumption Heterogeneity

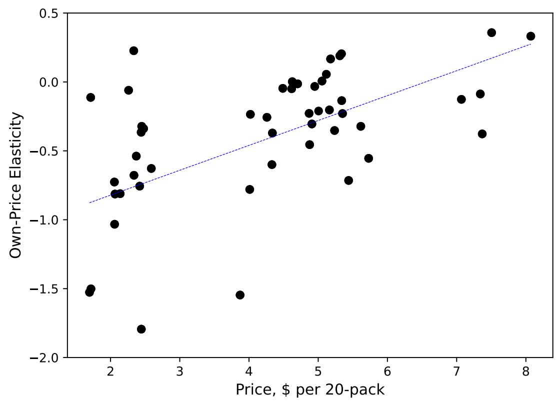
2.2.3 Firm Behavior: Low Elasticity & Tax Over-shifting

Elasticity It is also well-known that cigarette consumers are price inelastic. To explore this dimension without imposing strong shape restrictions on the demand, for each product j, I run the following regression:

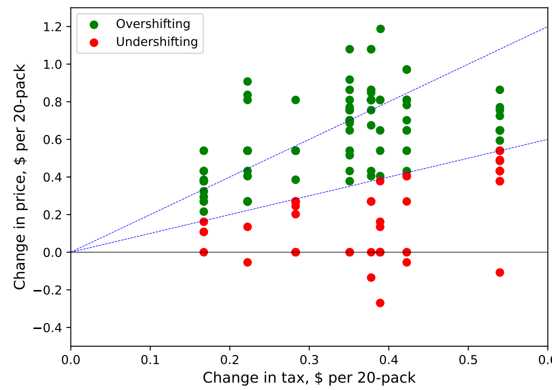
$$ln(q_{jt}) = \beta_j + \varepsilon_j ln(p_{jt}) + \sum_{r \neq j} \varepsilon_{jr} ln(p_{rt}) + t_t + \nu_{jt} \quad \forall j \in \{1, ..., J\} \tag{2.1}$$

where q_{jt} is the quantity of product j sold at time t, p_{jt} is the price of product j, t_t are time fixed effects, and ν_{jt} is an error term. I explore multiple specifications for this regression, including market and individual-level data and several fixed effects and instrumental variables approaches. Nonetheless, we acknowledge this is a descriptive regression only, and the results should be interpreted carefully.

Table B.1.2 presents the results of this regression for multiple specifications. In Figure 2.2a, I present the estimated own-price elasticity for each product in the sample. Two features are worth noting. First, the average elasticity is -0.3, which is low compared to most industries. In fact, it suggests that firms are pricing over the inelastic region of the demand curve, which is inconsistent with a standard model of static competition. Second, the elasticity is increasing with prices, suggesting that demand is more convex than the logit model would imply and that it has been observed in many industries.



(a) Elasticity, by product



(b) Pass-Trhough, by product and tax increase

Figure 2.2. Elasticity and Pass-Through

Pass-Through Finally, Figure 2.2b shows the pass-through of taxes for each product in the sample. The pass-through is defined as the percentage of the tax that firms pass to consumers. The average pass-through is 1.5, which implies that firms are over-shifting taxes– see Table B.1.2 for several pass-through regressions. Such a high pass-through indicates that the curvature of demand is likely to be high. Notably, it suggests that it is higher than one, the upper bound generated by the multinomial logit. However, Figure 2.2b also indicates substantial product heterogeneity. For instance, while some products tend to over-shift taxes by more than 200%, other products under-shift, absorbing up to 75% of the tax. This heterogeneity is consistent with the idea that firms consider the long-term implications of their pricing decisions.

2.3 Model

In this section, I present a dynamic model of competition under addiction. To simplify notation, we assume firms produce one product. The industry evolves over discrete time in an infinite horizon. We denote each period by $t \in \mathbb{N}$. There are F firms that make price decisions over J products. Consumers' choice set at t is $\mathbb{J}_t \in \{0,1\}^J$, with $\mathbb{J}_{jt} = 1$ if product j is offered at t.

2.3.1 Demand

Utility Consumers choose their preferred cigarette and how many units to consume or not to smoke. Consumer i's utility at period t from product j depends on the state $z \in \{1, ..., N\}$, i.e., the product they patronize the previous period, or $z = 0$ if they have no affiliation, and the number of cigarettes consumed in the past $q_{i,t-1}$.

$$\begin{aligned} & u_{ijt}(z, \mu^D) = x_j\beta_i + \alpha_i f(y_i, p_{jt}, q_{i,t-1}) + \eta_0 + 1\{z \neq 0\}\eta_1\{z = j\} + \xi_{jt} + \epsilon_{ijt} \quad \text{if } j \neq 0 \\ & u_{i0t}(z, \mu^D) = \epsilon_{i0t} \quad \text{otherwise} \end{aligned} \tag{2.2}$$

(x_j, ξ_{jt}) are observable and unobservable characteristics of the products. Furthermore, consumers' utility is state-dependent. $f(y_i, p_{jt}, q_{i,t-1})$ specifies how income y_i, prices p_{jt} and individuals' past consumption $q_{i,t-1}$ enter the indirect utility. The shape of f is crucial to determine the intensity of consumption. Moreover, individuals get extra utility η_0 (if positive) from consuming any inside goods if they were smoking previously. We coin this term "the extensive margin of 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". I introduce this loyalty parameter to account for the persistent product choices observed in Table 2.1. ϵ_{ijt} is a type I extreme value error term.

Intensive margin - Quantities smoked Following Birchall and Verboven (2022), I let $f(.)$ enter the utility function through a Box-Cox transformation.

$$f(y_i, p_{jt}, q_{i,t-1}) = g_i(A_{i,t-1})\frac{y_i^\lambda - 1}{\lambda} - \frac{p_j^\lambda - 1}{\lambda}$$

Our innovation is to introduce $g_i(q_{i,t-1})$, which captures the valuation that consumers make of income relative to the utility of consuming cigarettes. In particular, $g_i(.)$ is a decreasing function of previous consumption, and it might be individual-specific. To that extent, when $q_{i,t-1}$ is large, the relative valuation of income with respect to cigarette consumption is low. In particular, letting $g_i(q_{i,t-1}) = h_i(q_{i,t-1})^{\lambda-1}$, I micro-found the fact that consumers might spend different proportions to their income, $h(q_{it})$, depending on their stock of addiction. Non-addicted consumers assign a negligible proportion of their income to cigarettes, while highly addicted consumers will spend a higher fraction of their income. In that sense, we call the function $g_i(q_{i,t-1})$ the "intensive margin of addiction". Indeed, *Roy's identity* determines the quantity of cigarettes consumed, conditional on selecting product j:

$$q_{ijt}(y_i, p_{jt}, q_{i,t-1}) = -\frac{\partial u_{ijt}/\partial p_{jt}}{\partial u_{ijt}/\partial y_i} = \left(\frac{h_i(q_{it-1})y_i}{p_{jt}}\right)^{1-\lambda} \tag{2.3}$$

$\lambda \leq 1$ is the Box-Cox parameter. This parameter allows for flexible relationships between prices, income, and past consumption with current consumption. If $\lambda = 1$, income enters linearly, and consumers purchase one unit of their preferred product. More generally, all functions $f(y_i, p_{jt}, q_{i,t-1}) = \tilde{f}(y_i - p_{jt}, A_{it})$ imply unit demand and have recently been utilized to introduce non-linear income effect without departing from the unit demand framework (Griffith et al., 2018; Miravete et al., 2023). For $\lambda < 1$, $f(.)$ becomes a convex function on prices and past consumption. Therefore, quitting additional cigarettes becomes increasingly harder as prices rise. The model converges to the CES demand specification as $\lambda \to 0$. I assume no observed or unobserved preference heterogeneity exists beyond past choices and consumption. That is, I assume $\beta_i = \beta$ and $\alpha_i = \alpha$.

Extensive margin - Choice probabilities Next, I aggregate individual-specific utility components to obtain the conditional choice probabilities. Let

$$u_{ijt} = K_{it} + \delta_{jt} + \eta_0 1\{z \neq 0\} + \eta_1 1\{z = j\} + \epsilon_{ijt} \tag{2.4}$$

where $K_{it} = \alpha h_i(q_{i,t-1})^{\lambda-1}\frac{y_i^{\lambda}-1}{\lambda}$, $\delta_{jt} = x_j\beta - \alpha\frac{p_{jt}^{\lambda}-1}{\lambda} + \xi_{jt}$.

Let $\bar{u}_{ijtm}(z;\theta^D) = \delta_{jt} + \eta_0 1\{z \neq 0\} + \eta_1 1\{z = j\}$, and assume ϵ_{ijt} 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,

$$s_{ijt}(z;\theta^D) = \frac{exp(\bar{u}_{ijt}(z,\theta^D))}{1 + \sum_k exp(\bar{u}_{ikt}(z,\theta^D))} \tag{2.5}$$

where $\theta^D = \{\beta, \alpha, \lambda, \xi\}$ and K_{it} cancels out from choice probabilities of specific products.

Aggregate Demand Then, market-level shares on the entire distribution of past product choices and consumption quantities. We express them as

$$Q_{jt}(\theta^D) = \int \underbrace{s_{ijt}(z;\theta^D) q_{ij}(y_i, p_{jt}, q_{i,t-1})}_{Q_{ijt}(z, y_i, p_{jt}, q_{i,t-1})} dF(q_{i,t-1}, z)$$

Aggregating markets share under affiliation z such that $Q_{jt}(z,\theta^D) = s_{ijt}(z;\theta^D)\int q_{ij}(y_i, p_{jt}, q_{i,t-1})dF(q_{i,t-}$ and taking into consideration that affiliation is a discrete random variable, aggregate market shares can be expressed as

$$Q_{jt}(w;\mu^D) = \sum_{z\in\{1,\dots,J\}} w_t(z)Q_{jt}(z;\theta^D) + w_t(0)Q_{jt}(0;\theta^D)$$

where $w_t(z) = S_{z,t-1}$.

Under these assumptions, demand at t is a function of prices, lagged market shares $S_{t-1} \in [0,1]^{F\times N}$ and the distribution past quantities for every product $dF(q_{i,t-1}|z)$, taking into consideration the available choice set, $\mathbb{J}_t$.

$$Q_{jt} = Q_{jt}(p_t, S_{t-1}, \mathbb{J}_t, dF_{q|z}; \theta^D) \tag{2.6}$$

Discussion We simplify consumer preferences in two dimensions. First, we depart from classic rational addiction models (Becker and Murphy, 1988) and assume individuals are myopic. This assumption is not uncommon in the literature –see, for instance, Tuchman (2019)– and it arises from the challenge to differentiate it from forward-looking behavior empirically.[4] Moreover, Arcidiacono et al. (2007) shows that the distinction between myopic and forward-looking behavior has almost identical implications for the estimation of addiction. Second, we assume there is no observed or unobserved persistent preference heterogeneity in addition to that defined by past consumption choices. Introducing unobserved persistent heterogeneity would also increase the size of the state substantially as it expands the number of consumer types to evaluate. Note, however, that we allow for substantial observable individual heterogeneity by keeping track of individuals' stocks of addiction.

[4]There is, however, some evidence in favor of rational addiction (Becker and Murphy, 1988; Chaloupka and Warner, 2000; Gruber and Köszegi, 2001; Arcidiacono et al., 2007)

2.3.2 Supply

Setup

Variable Profits Prices, demand, and marginal production costs (c_{ft}) determine firms' per-period profits $\pi_j(p_t, S_{t-1}, \mathbb{J}_t, dF_{q|z}; c_{ft}; \theta^D) = (p_{jt} - c_{jt})Q_{jt}(p_t, S_{t-1}, \mathbb{J}_t, dF_{q|z}; \theta^D)$. We assume that all firms' marginal costs c_{jt} 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 $c_{jt} = c_t + c_j$. 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. Differently from Pareschi and Lopez (2024), we assume the choice set evolves exogenously.

State Space & Transitions The payoff relevant variables are the joint distribution of product market shares and stocks of addictions and marginal costs, and time-varying consumer preferences: $\mathbb{X}_t = (S_{t-1}, d_{q|z}, c_t, \delta_t)$. c_t and δ_t evolve exogenously from any firm's action. The evolution of S_{t-1} and $d_{q|z}$ is endogenous and entirely determined by the demand function.

Firms Objective Firms set prices to maximize expected discounted profits.

$$\max_{p_f} \mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \left\{\pi_f(p_\tau, S_{\tau-1}, \mathbb{J}_\tau, dF_{q|z}, c_\tau, \delta_\tau)\right\} |\mathbb{X}_t\right] \tag{2.7}$$

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

Equilibrium

Markov Strategies In a Markov Perfect Equilibrium (MPE), firms' behavior depends on the payoff relevant states. A Markov strategy for firm f is a function $\sigma_f : \mathcal{X} \rightarrow \mathcal{A}_f$, where $\mathcal{X}$ is the support of the commonly observed states and $\mathcal{A}_f$ is the support of the actions. A profile of Markov strategies is $\sigma = (\sigma_1, ..., \sigma_N)$ with $\sigma : \mathcal{X}\times \rightarrow \mathcal{A}$. 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}.

Oblivious Equilibrium Note, however, that the MPE is not a suitable equilibrium concept in our setting. The payoff relevant variables are determined by the joint distribution of market shares by product and individuals' addiction stock, time-varying marginal costs, and mean cigarette valuation. Suppose, for instance, ten relevant products are in the market, and we can summarize addiction stocks by four grid points. Even if we work with a coarse approximation of the value function using ten grid points, the state space would be approximately $11^{(10\times4)}$ plus the size of the exogenous shocks. Neither researchers nor market participants can track this state space for computational reasons.

We define an alternative equilibrium concept based on Weintraub et al. (2008)'s Oblivious Equilibrium (OE) to alleviate these computational constraints and make progress on the empirical application. Under our approach, firms' best responses depend only on their own state, which, in this case, is given by the distribution of addiction within their product and the exogenous shocks. This assumption already reduces the state space to $11^{(4)}$ plus the size of the exogenous shocks. Moreover, they assume that rival states are fixed–in particular, this implies they cannot affect their evolution–and distributed according to the stationary distribution observed in the recurrent class of the game. In addition, we assume firms do not track the entire distribution of past consumption conditional on product choices but only the average consumption. This assumption implies that a firm could not differentiate between two consumers smoking 20 cigarettes daily and one smoking 10 and the other thirty.

Formally, firm f tracks the total quantities sold by its own products in the last period $Q_{f,t-1}$. In addition, firms have perfect information about the common component of costs and mean valuations for cigarettes: $\xi_t = (c_t, \delta_t)$. Oblivious strategies are functions from the space information set (Q_{ft}, ξ_t) to the space of actions: $\tilde{\sigma}_f = \tilde{\sigma}_f(z_t, \xi_t) : \mathcal{I}_f \to \mathbb{R}$. Then, transition kernels are defined as follows. The transition kernel of ξ_t is known and does not require any approximation. On the other hand, firms' f transition kernel of next period market shares, when firm f plays oblivious strategy $\tilde{\sigma}^p_f$ and rivals play $\tilde{\sigma}^p_{-f}$ is defined by

$$Q^e(Q_{f,t-1}, \xi_t; \tilde{\sigma}) = E\left[Q_{ijt}(s_{j,t-1}, q_{i,t-1}, \mathbb{J}, p_{ft}, p_{-ft}) | Q_{f,t-1}, \xi_t; \tilde{\sigma}\right] \tag{2.8}$$

The expectation is taken over past market shares, individual-specific consumption levels, and rivals' prices. I follow the intuition in Weintraub et al. (2008); Fershtman and Pakes (2012) and Ifrach and Weintraub (2017) to construct this expectation. Concretely, firms draw realizations of last period market shares and the distribution of past consumption from the long-run distribution of states over the recurrent class, which we can forward-simulate from any guess of firms' strategies $\tilde{\sigma}$. Naturally, firms condition on their information set, which makes some distributions more likely than others. Then, for each realization of market shares, it is easy to construct a corresponding realization of rivals' information set $(Q_{-f,t}, \xi_t)$ since it implies summing over different groups of quantites. Finally, firms need to evaluate rivals policies $\tilde{\sigma}_{-f}$ at such realizations of rivals' information set to construct a realization of rivals' prices $p_{-f}(Q_{-ft}, \xi_t)$. The construction of expected static profits is analogous.

If firm behavior is given by an Oblivious Strategy $\tilde{\sigma}$, then the value function when firm f plays a moment-based strategy $\tilde{\sigma}'_f$ and rivals follow strategies $\tilde{\sigma}_{-f}$ is,

$$\tilde{V}_f(Q^{f,t-1},\xi_t|\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) = \max_{p_f} \pi^{e(f)}(Q_{f,t-1},\xi_t;p_f,\tilde{\sigma}_{-f}) + \beta \int V_f(Q_{f,t},\xi_{t+1}|\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) dF(Q_{f,t+1},\xi_{t+1}|Q_{ft},\xi_t,\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) \tag{2.9}$$

Then, we can define our equilibrium concept:

Definition 2 ***Oblivious Equilibirum***

The equilibrium consists of

1. *Price strategies* $\tilde{\sigma} : \mathcal{I} \to R^F$

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* $Q_{f,t-1}, \xi_t$: $\{\tilde{V}_f(Q_{ft-1},\xi_t|\tilde{\sigma}'_f,\tilde{\sigma}_{-f}) for f \in \{1,...,F\}\}$

such that

1. *Strategies* $\tilde{\sigma}^*_f$ *are optimal when rivals behave according to* $\tilde{\sigma}^*_{-f}$ *at every information set* (Q_{ft},ξ_t) *for all* f

2. *Firms' beliefs are consistent with equilibrium play in the sense of Equation 2.8 and Equation 2.9.*

2.3.3 Properties of the Model

Now, I derive the main implications of the model for pass-through. First, I derive the demand manifolds, that is, the relationship between the elasticity and the curvature of demand–see Mrázová et al. (2021) and Miravete et al. (2023) for a discussion of the concept. Then, I show how the dynamic competition model affects equilibrium elasticity and firms' pass-through.

Demand Manifolds

The introduction of the intensive margin of consumption substantially modifies the possible curvatures of demand. In particular, the box-cox parameter λ determines a wide array of possible elasticity-curvature relations. Next, I derive the demand manifolds, that is, the relationship between the elasticity and the curvature of demand–see Mrázová et al. (2021) and Miravete et al. (2023) for a discussion of the concept. The analysis in this section shows what combinations are feasible for any level of prices. In the next section, I describe how dynamic incentives determine equilibrium outcomes.

The derivative of the individual-level demand is

$$\begin{aligned}\frac{\partial Q_j}{\partial p_j} &= \int \frac{\partial Q_{ij}}{\partial p_j} dF(i) = \\ &= -\int \alpha_i p_j^{\lambda-1} s_{ij}(1-s_{ij})q_{ij} + (1-\lambda)\frac{s_{ij}q_{ij}}{p_j} dF(i) \\ &= -\int Q_{ij}\left(\alpha_i(1-s_{ijt})p_j^{\lambda-1} + \frac{(1-\lambda)}{p_j}\right) dF(i)\end{aligned} \tag{2.10}$$

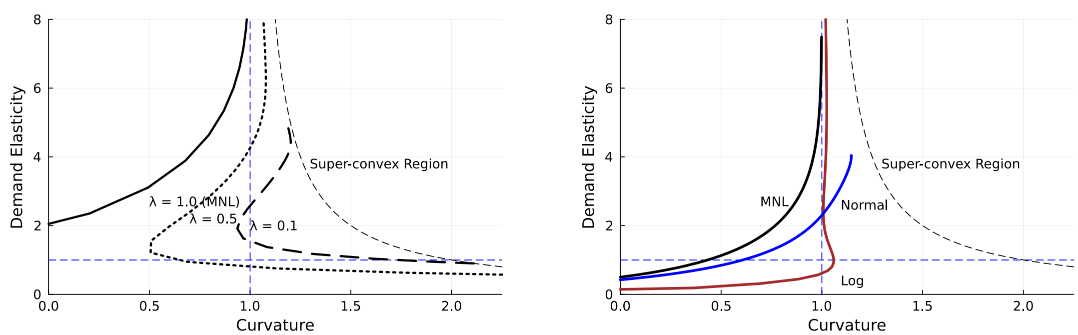
And the own price elasticity is,

$$\epsilon_{jj} = -\int \frac{Q_{ij}}{Q_j}\left(\alpha_i(1-s_{ijt})p_j^{\lambda} + (1-\lambda)\right) dF(i) \tag{2.11}$$

The parameter λ calibrates the relationship between elasticity and prices. If $\lambda = 0$, then there is no scaling. On the other hand, when $\lambda = 1$, the model boils down to the logit model and the elasticity scales linearly with prices. More generally, if $\lambda < 0$, elasticities scale less than linearly with prices. The curvature of demand defines this relationship more formally:

$$\begin{aligned}\frac{\partial^2 Q_j}{\partial p_j^2} &= \int \left(\frac{\partial^2 q_{ij}}{\partial p_j^2} s_{ij} + 2\frac{\partial q_{ij}}{\partial p_j}\frac{\partial s_{ij}}{\partial p_j} + q_{ij}\frac{\partial^2 s_{ij}}{\partial p_j^2} \right) dF(i) \\ &= \int (1-\lambda)(2-\lambda)\frac{Q_{ij}}{p_j^2} + (1-\lambda)\alpha_i \frac{Q_{ij}}{p_j^2} p_j^{\lambda}(1-s_{ij}) + \alpha_i \frac{Q_{ij}}{p_j^2}(1-s_{ij})\left((1-\lambda)p_j^{\lambda} + \alpha_i p_j^{2\lambda}(1-2s_{ij})\right) dF(i)\end{aligned} \tag{2.12}$$

It is evident from Equation 2.12 that the function $f(y_i, p_{jt}, q_{i,t-1})$, which determines how addiction, income, and prices enter the indirect utility function, heavily influences the curvature of demand. In the logit case ($\lambda = 1$), the curvature boils down to $\frac{(1-2s_j)}{1-s_j} <= 1$. Figure 2.3a compares the manifolds generated by the logit model, the CES model, and several intermediate values of $\lambda \in (0,1)$. First, note that the curvature of the logit model is never larger than one and that the relationship between elasticity and curvature is increasing. On the other hand, the CES demand function presents a negative correlation between curvature and elasticity. In the model, the demand becomes increasingly more "convex" as we decrease λ. Therefore, for low values of λ, we can generate combinations of low elasticity and high curvature, as appears to be the case in the Uruguayan cigarette market.



(a) Intensive Consumption

(b) Mixed logit with heterogeneous α_i

Figure 2.3. Demand Manifolds

However, alternative demand models can generate similar combinations. In particular, we can relax the logit model's restrictions by introducing heterogeneity in the disutility from prices α_i. In this case, the curvature of demand is $\rho^{\alpha_i}(p) = \frac{p_j^2}{\epsilon_{jj}^2 S_j} \int \alpha_i^2 (1 - 2s_{ij}) dF(i)$. Miravete et al. (2023) illustrates the manifolds generated under this specification for several distributions of α_i, and I replicate some of them in Figure 2.3b. Although the manifolds can cross into the long-convex region of demand for reasonable distributions, they tend to preserve the positive correlation between elasticity and curvature. Consequently, in these models, low elasticity is generally associated with low curvature and vice versa.[5]

Equilibrium Prices

The manifolds illustrate the possible combinations of elasticity and curvature that we can get for a particular demand model at some price. Nevertheless, the equilibrium prices result from the equilibrium of a dynamic game the firms play. In this section, I characterize firm strategies and how they shape equilibrium prices and pass-through.

Firms choose prices to maximize their long-run profits. We determine firms' best responses by taking the FOC of Equation 2.9 with respect to prices.

$$p_{jt} = \underbrace{\left(c_{jt} - \beta \frac{\partial \tilde{V}_f(Q^e_{ft}, \xi_t)}{\partial Q^e_{ft}} \right)}_{\text{Virtual Costs}} - \underbrace{\frac{Q^e_{ft}}{\frac{\partial Q^e_{jt}}{\partial p_{jt}}}}_{\text{Static Markup}} \tag{2.13}$$

Equation 2.13 indicates that firms mark up some measure of their cost following a rule that depends on the elasticity of demand. However, the key difference is that when there is habit formation, customers become a valuable asset that firms invest in. An additional customer of product j changes firm f discounted expected long-term profits by $\psi_{fj} = \beta \frac{\partial \tilde{V}_f(Q^e_{ft}, \xi_t)}{\partial Q^e_{ft}}$. ψ_{fj} is the value of an additional customer of product j to firm f. In the model, firms invest in bringing consumers to their products by decreasing prices. Therefore, the additional value of a customer to the long-term profits of the firm enters the price FOC as the negative of a cost.

[5] Birchall and Verboven (2022) shows that mixed logit models generally generate a U-shape relationship between elasticity and prices

We follow Besanko et al. (2010) and call the difference between the marginal costs and this additional value *virtual costs*. An increase in the incentives to invest in the customer base is equivalent to a decrease in the virtual cost of serving them. Then, firms mark up virtual costs based on consumers' elasticity. However, note that these markups are a function of the products' locked-in customer base. The more customers a firm has, the more inelastic the residual demand is, and the higher the markup firms want to set. In other words, if a firm has more locked-in customers, it can extract more value from them; that is, it can "harvest" them more. Thus, Equation 2.13 recast the well-known investing and harvesting incentives (Farrell and Klemperer, 2007) into a FOC that resembles the usual inverse elasticity pricing rule:

$$\frac{p_{jt} - \left(c_{jt} - \beta \frac{\partial \tilde{V}_f(Q^e_{ft}, \xi_t)}{\partial Q^e_{ft}}\right)}{p_{jt}} = -\frac{1}{\epsilon^e_{jj}} \tag{2.14}$$

Equation 2.14 is broadly discussed in Pareschi and Lopez (2024). There, we show that firms set prices such that the elasticity of demand is low, potentially below one, to invest in the customer base and exploit the long-term profits a consumer generates.

Pass-Trhough

Then, I use the implicit function theorem to derive the pass-through of prices to costs. Observe that our equilibrium definition is necessary to derive this relationship. In particular, it is crucial to assume that firms are "almost" monopolists in their own product as it eliminates the dependence between rivals' strategies on firms' own prices.[6] Under this assumption, the pass-through of prices to costs is approximately given by[7]

[6]This is not strictly true in the Oblivious Equilibrium since firms' strategies depend on rivals' strategies through stationary outcomes over the recurrent class. Therefore, these relationships should be considered an approximation of the true pass-through.

[7]I'm also assuming firms produce a single product. Setting up the relevant equations for the case of multiproduct firms is straightforward.

$$\frac{dp}{dc} = \frac{1 - \beta \frac{\partial^2 \tilde{V}_f(Q^e_{jt}, \xi_t)}{\partial Q^e_{jt} \partial c_t}}{2 - \rho(Q_{jt-1}, \xi_t) + \beta \frac{\partial^2 \tilde{V}_f(Q^e_{jt}, \xi_t)}{\partial (Q^e_{jt})^2} \times \frac{\partial Q^e_{jt}}{\partial p_{jt}}} \tag{2.15}$$

The pass-through equation in Equation 2.15 modifies the usual formula for a static monopoly by accounting for the change in the long-term incentives to invest in the customer base. Overall, Equation 2.15 indicates that the pass-through in this dynamic quasi-monopoly is determined by the relative strength of the change in the incentives to harvest (curvature, captured by $\rho(Q_{jt-1}, \xi_t)$) and the change in the incentives to invest in consumers. The incentives to invest are captured by the cross-partial derivative of the value function with respect to quantities and costs, as well as the cross-partial between prices and quantities. The introduction of dynamic incentives allows rationalizing low pass-through in the presence of high curvature (if a firm has incentives to invest in expanding its customer base) and high pass-through in the presence of low curvature (if the long-term value of customers as we increase costs goes down). Hence, it is easy to see that accounting for dynamic incentives is crucial to capture the high degree of heterogeneity in pass-through observed in the data.

2.4 Identification & Estimation

In this section, I lay out the identification strategy. I first discuss the identification of consumer preferences and then move to the supply side.

2.4.1 Consumer Preferences

The panel of smokers provides a rich source of variation to identify the elasticity and curvature of demand. In particular, I identify the Box-Cox parameter λ from the correlation between the number of cigarettes consumed, prices, income, and past consumption levels. In Section 2.3.1, I show that conditional on choosing product j at period t, individual i would consume q_{ijt} units of the product according to the following relationship

$$q_{ijt}(y_i, p_{jt}, q_{i,t-1}) = \left(\frac{h_i(q_{it-1})y_i}{p_{jt}}\right)^{1-\lambda}$$

Thus, we parametrize $h_i(q_{it-1}) = (1 - e^{\eta_2 q_{i,t-1} + x_i\gamma}) \times e^{\omega_{it}}$, where x_i are some observable individual characteristics and ω_{it} is a structural error, which might depend on unobservable individual characteristics. Then, we can define the following econometric relationship

$$log(q_{ijt}) = (1-\lambda) \times log(\Big(1 - e^{\eta_2 q_{i,t-1} + x_i\gamma}\Big)) + (1-\lambda) \times log(\frac{y_i}{p_{jt}}) + \tilde{\omega}_{it} \tag{2.16}$$

In principle, $\tilde{\omega}_{it}$ can be correlated with unobserved individual characteristics, which are, in turn, correlated with past consumption $q_{i,t-1}$. Therefore, the construction of moments from $E[\tilde{\omega}_{it}|q_{i,t-1}, x_i, y_i, p_{jt}]$ is likely to lead to biased and inconsistent estimators. Therefore, I explore several fixed effects, first difference, and instrumental variable strategies to identify the parameters of interest. In Section 2.5, I show results are robust to these alternative specifications.

Identifying the extensive dimension of addiction and brand loyalty, for any value of λ, follows from Pareschi and Lopez (2024), and I refer the reader to their work. There, the authors show that the Uruguayan experience provides rich variation in taxes and choice sets, which allow us to separately identify habit formation from mere price responses or persistent preference heterogeneity.

2.4.2 Supply

Studying tax policy requires identifying and estimating how firms' dynamic incentives change with the tax regime. The classic approach to do so requires determining firms' beliefs and then solving the equilibrium of the game under the observed, assumed or estimated primitives. MacKay and Remer (2021) proposes an alternative approach to recover the necessary dynamic components in reduced form. The key idea is to approximate the derivative of the value function with respect to quantities using the price first-order conditions.

Assume costs are determined by taxes plus an unobservable log-normal measurement error.[8] Then, using the data and the estimated demand parameters, I estimate the following dynamic FOC:

$$\left(\frac{Q_{jt}}{\frac{\partial Q_{jt}}{\partial p_{jt}}} + p_{jt} - tax_t \right) = \Phi_j(Q_{jt}, tax_t, \delta_t) + \zeta^1_{jt} \tag{2.17}$$

Equation 2.17 uses $\Phi_j(Q_{jt}, tax_t, \delta_t)$ to approximate the derivative of the value function with respect to quantities. The key identifying assumption is that the measurement error ζ is uncorrelated with the states.[9]

Finally, I observe that pass-through equations can improve the identification of dynamic incentives by restricting the cross-partial derivatives of the value function. These restrictions are particularly beneficial in counterfactuals, where we rely on parametric extrapolations. The multiple tax changes in the dataset allow me to compute a measure of $\frac{dp}{dc}$. Then, I can use the theoretical pass-through and demand estimates to recover the change in the investing incentives:

$$log(\frac{dp_{jt}}{dc_t}) = log\left(1 - \Psi^c_f(Q_{jt}, tax_t, \delta_t)\right) - log\left(2 - \rho_{jt} + \Psi^Q_f(Q_{jt}, tax_t, \delta_t) \times \frac{\partial Q_{ft}}{\partial p}\right) + \zeta^2_{jt} \tag{2.18}$$

As before, $\Psi^c_f(Q_{jt}, tax_t, \delta_t)$ and $\Psi^Q_f(Q_{jt}, tax_t, \delta_t)$ in Equation 2.18, approximate the cross-partial derivative of the value function of firm f with respect to quantities and costs, and the second derivative with respect to quantities respectively. Note also that ρ_{jt} can be easily

[8] This assumption is less restrictive than it might seem at first sight. First, Pareschi and Lopez (2024) estimates firms' marginal costs and finds that approximately 90% is given by taxes.

[9] Observe we do not need to take a stance on the value of the discount factor β

computed from data and demand estimates. The crucial identifying assumption is that ζ^2_{jt} is conditionally independent of states.

2.5 Structural Estimates

2.5.1 Consumer Preferences

Results from individual regression in Equation 2.16 indicate that the intensive consumption margin plays a significant role. We can reject the null hypothesis that the Box-Cox parameter equals 1, i.e., that our model boils down to a mixed logit with unit demand. In fact, our estimates suggest that the demand function is closer to a CES with a value of $\lambda = 0.2141$.

	log(q)
$log\left((1 - e^{\eta_2 A_{i,t-1}}) \times \frac{y_i}{p_{jt}}\right)$	0.7859***
R-squared Adj.	0.8087
Number of obs	1686

As I mentioned in Section 2.4, for any value of λ, we can estimate the remaining consumer primitives following the empirical strategy laid out in Pareschi and Lopez (2024). Here, I replicate the results obtained for $\lambda = 1$ as a relevant benchmark. Inertia over the extensive margin is significantly high. Indeed, smokers are typically willing to pay almost two times the average price for any cigarette. Furthermore, they are prepared to spend about three times the average cigarette price to maintain their product choice. Naturally, firms do not solely target repeat customers, enabling these consumers to pay lower prices than they are willing to pay. There is also a modest amount of consumer heterogeneity. Specifically, educated and younger customers are less sensitive to price and prefer light products more. Table 2.2 presents a summary of consumer preference estimates. These estimates suggest that the mean own-price elasticity in the market is relatively low, around -0.9, in line with our descriptive results in Section A.1 – see Table B.1.3.

		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		

Note: This table replicates results in Pareschi and Lopez (2024).

Table 2.2. Demand Estimates

2.5.2 Dynamic Incentives

We can then construct $(Q_{jt}/\frac{\partial Q_{jt}}{\partial p_{jt}} + p_{jt} - tax_t)$ leveraging these estimates, and regress these values on a flexible function of the states Q_{jt}, tax_t, and δ_t as in Equation 2.17. Table 2.3 presents the average values of the derivatives of the value function with respect to quantities and its cross-partial derivatives. There is significant heterogeneity in the incentives to invest in sales. For instance, it is more profitable to invest in consumers of the national firm flagship product than in attracting consumers to relatively less popular products such as the BAT premium brands.

Product	$\frac{dV}{dQ}$	$\frac{d^2V}{dQ^2}$	$\frac{d^2V}{dQd\tau}$
MP Flag.	3.36	10.4	0.99
MP Regular	0.64	16.86	0.27
MP Light	1.01	15.66	0.27
MP Specials	0.23	17.26	0.27
PM Flag.	1.92	12.91	0.27
PM Light	0.77	16.4	0.27
PM specials	0.39	17.25	0.27
BAT Regular	0.88	17.01	0.27
BAT Premium	0.39	17.22	0.27

Table 2.3. Structural Estimates of Investing Incentives and Cross-Partial Derivatives

Table 2.3 also presents the average estimates of the cross-partial derivatives of the investing incentives respect to quantities and costs. First, these results suggest that the value function is convex, since the investment incentives increase in past sales. Perhaps surprisingly, our results indicate that firms have slightly higher incentives to invest at higher costs. The intuition for this result is that the remaining sales will come from less elastic, more profitable consumption at higher costs.

2.5.3 Pass-Through and Incidence

Next, I use the demand and supply estimates to simulate the pass-through of taxes to prices. The results suggest that the pass-through is high, in line with our pass-through regressions in Table B.1.2. We can further compare the simulated pass-through of forward-looking and myopic firms. In the static case, without considering the change in the incentives to invest as the government increases taxes, the simulated pass-through is around 1.3. Instead, in the dynamic case, the pass-through goes up 40% to 1.93 on average. By looking at Table 2.3, we can see that firms pass more of the tax to prices because the value of investing at lower quantities decreases. This effect is stronger than the effect caused by the increasing incentives to invest due to increased firms' costs, as I previously discussed.

	Static	Dynamic
$\frac{dp}{d\tau}$	1.3053	1.9281
$\%\nabla CS$	0.566	0.658
$\%\nabla PS$	0.434	0.342

Finally, I compute incidence formulas, following Weyl and Fabinger (2013). The pass-through rate ultimately determines incidence in the monopoly case. Higher pass-through implies that a higher share of the tax is passed on to consumers. The dynamic nature of the problem does not change this, although the expected pass-through is different. Our results show that consumers support approximately 56.6% of the total surplus loss in the static case. In the dynamic case, the burden of the tax that falls on consumers is up to 65.8%.

2.6 Conclusion

In conclusion, I show that the distribution of quantities consumed critically informs the curvature of demand. Moreover, consumer addiction and brand loyalty affect the interaction between this curvature and firms' pass-through. Finally, we use this framework to explore the incidence of taxation in the tobacco industry. I find that forward-looking firms have incentives to pass more of the tax to prices, increasing the tax burden on consumers.

Chapter 3

How Do Governments Engage in Price Discrimination? Evidence from a Large-Scale Nationalization

3.1 Introduction

State-owned enterprises (SOEs) are prevalent across different industries. They account for 10% of the world's GDP and have doubled their presence among the world's largest corporations in the past decade (IMF, 2020). Recently, SOEs have been subject to policy debate in different countries. While some governments are discussing privatization or reform——as a way to enhance performance and alleviate the burden on taxpayers——others are proposing the creation of new government-owned firms to address problems that markets fail to solve. Overall, there are open questions regarding SOEs' social costs and benefits and how they perform under different institutional arrangements.

In this paper, we explore a crucial tradeoff around state ownership: SOEs have the potential to correct market failures, but they might be subject to the influence of politics and interest groups, thereby diverting their actions from the public interest (Stigler, 1971). Political interventions can manifest in various ways. For example, politicians may leverage SOEs for patronage, cross-subsidizing towards specific groups, and aiming for electoral gains. Alternatively, external parties like competitors or suppliers might lobby for favorable terms, escalating the firm's deficit and, by extension, the burden on taxpayers. In essence, the government's commitment to correct market failures is uncertain. Even in scenarios where SOEs enhance social welfare, there remains a significant risk that certain groups may disproportionately appropriate these gains, leading to an inequitable distribution of benefits. While the tradeoff between potential welfare gains and political capture is understood in the theoretical literature, empirical evidence is limited. Researchers often lack data and quasi-experimental variation to identify the effects of state ownership on market outcomes.

To fill this gap, we examine the nationalization of YPF, the leading gasoline company in Argentina. We estimate an oligopoly model of gasoline supply and demand and employ it to quantify the nationalization effects on welfare and distributional outcomes. Using elements from the conduct estimation literature, we develop an empirical strategy to estimate the government's objective function, which reflects its underlying preferences for redistribution as a function of political and demographic characteristics. We use our framework to inform policy design. In particular, we study the equilibrium responses of the SOE to pricing rules imposed by Congress that aimed to align the government's decisions with social welfare. We also use the model to analyze the effects of privatization.

The setting provides a unique opportunity to understand the effects of state ownership. Regarding data, we have access to a panel of monthly gasoline prices and sales for all gasoline stations in Argentina before and after the nationalization. In terms of quasi-experimental variation, the nationalization allows us to observe how a firm sets prices as a privately owned company and compare that to how the *same firm* sets prices when the government runs it.

Our descriptive analysis reveals that the government sets prices differently than a profit-maximizing firm in three dimensions. First, the government set lower prices on average. Gasoline prices decreased by 5%, and sales increased by 4% in the year following nationalization, with nearly 90% of this surge attributed to a rise in YPF's regular gasoline sales. Second, YPF implemented larger price cuts for products with less elastic demand and were likely to have higher markups. Supporting this assertion, we observed that YPF gasoline prices decreased relatively more in higher-income areas, in markets where YPF had a higher pre-nationalization market share, and in premium gasoline products (compared to regular gasoline products). Third, YPF changed the relative prices of gasoline across geographical regions. In particular, gasoline became more affordable in provinces that cooperated with the federal government during the expropriation process and were allowed to retain 25% of YPF's stocks after the nationalization (henceforth referred to as *shareholder provinces* or *provinces with political ties*).

Collectively, these findings underline a fundamental tradeoff inherent in public ownership. On the one hand, the firm takes measures that benefit consumers and boost allocative efficiency. After the nationalization, the firm exercises less market power, charging lower prices and expanding aggregate consumption. Moreover, it engages in price discrimination differently than a profit-maximizing firm. A profit-maximizing firm engages in price discrimination by charging higher prices to consumers with a higher willingness to pay. In contrast, the nationalized firm charges prices that are less correlated with consumers' willingness to pay, generating a better alignment between prices and costs. We refer to this as a reduction in *economic price discrimination*. On the other hand, the state-owned company engages in price discrimination based on consumers' political characteristics. In our study, this arises from the differential influence of consumer representatives (e.g., governors) on the firm's decision-making process. We refer to this as *political price discrimination*.

Based on the main descriptive facts, we formulate and estimate an oligopoly model of gasoline supply and demand. On the demand side, consumers purchase gasoline products. Gasoline products are differentiated based on geographic location, station-specific, and product-specific attributes. On the supply side, companies choose gasoline prices for different geographic locations. After the nationalization, we assume all firms except the SOEs maximize profits. The SOE maximizes a welfare function that is unobservable to the econometrician and that we recover from data. The parameterization of the objective function encompasses both the profit-maximization case and the total surplus maximization case. It also allows for an array of intermediate cases in which the SOE has preferences for some groups of consumers and firms over others, reflecting different possible political motives behind the government intervention.

Through the lens of our model, the nationalization of YPF represents a shock to the objective function of the firm. At the same time, prices might have also changed due to changes in their underlying determinants, such as changes in crude oil prices or consumers' willingness to pay for gasoline products. To understand the effects of the nationalization, we need to account for changes in costs and consumer preferences contemporaneous with the nationalization. Disentangling demand-side explanations, cost-side factors, and changes in objective functions pose an identification challenge. The nationalization provides rich variation to address it.

Our identification strategy exploits the fact that individuals from different demographic groups have different consumption patterns. They consume gasoline at different locations, usually close to where they live or work, and have different preferences for premium gasoline products, which are almost exclusively consumed by middle and high-income households. This gives the government various tools to target specific consumers and reveal preferences for some groups over others by charging lower prices. Similar arguments apply to preferences for firms. We use this variation to construct an instrument that shifts the government's objective function in the post-nationalization period (Berry and Haile, 2014). Following Miller and Weinberg (2017), we leverage pre-nationalization data and the fact that most market participants are profit-maximizing firms to recover marginal costs for all companies in the pre-nationalization period and for all firms except YPF in the post-nationalization period. Using this information, we project YPF's costs in the post-nationalization period.

After identifying costs and demand primitives, we compute the prices that a profit-maximizing firm would have charged under the same conditions and compare them to the prices set by the state-owned firm. Finally, the difference between *observed* and *profit-maximizing prices*, and specifically, how this difference changes across products of different qualities and in different geographic zones, allow us to identify the government's preferences.

Our estimates of the objective function reveal political motives behind the nationalization. In comparison to a benevolent planner that internalizes the welfare of all consumers and firms equally, we find higher internalization of the welfare of middle-income consumers in all provinces—who benefit from lower economic price discrimination—–and higher internalization of consumers in provinces with political ties with the firm —–who benefit from political price discrimination. The objective function also indicates that YPF does not internalize the effect of its pricing on rivals' profits.

Using our model, we find that, compared to a profit-maximizing firm, the SOEs charge 6% lower prices on average, increasing gasoline sales by 4% and consumer welfare by 12%. As previously documented in the literature, equilibrium effects play an essential role. YPF's rivals also reduce prices in response, especially for lower-quality products, making the impact on sales even larger. Consistent with descriptive evidence, the nationalization is associated with more homogenous markups within provinces. This means more homogeneity between markups in high and low-income zones and between more and less concentrated markets. However, the nationalization also led to more dispersion in markups across provinces. In particular, the nationalization led to relatively lower markups in shareholder provinces, which are politically connected with the firm. Overall, the nationalization increased total welfare by 6%, but its gains are unequally distributed across different members of society.[1]

In the last part of the paper, we explore different policy tools to align government actions with social preferences, limiting the influence of politics and interest groups in government

[1]This computation does not consider the marginal value of public funds. We are working on a sensitivity analysis using estimates for Argentina.

decision-making. In many countries, state-owned enterprises are subject to regulations that reduce government discretion in setting prices. Common examples are uniform pricing rules that require the firm to charge the same price for the same product or the same wage for the same position. Additional examples are price rules that tie prices to observable variables (such as costs or price indexes).[2]

To evaluate the effects of the proposed policies, we solve YPF's pricing problem by considering their preferences —denoted by our estimates of its objective function— yet restricting YPF's choice set by the price rule. We examine the effects of three regulatory approaches. The first regulatory approach, *uniform pricing*, involves setting equal prices for identical products at every gasoline station. The second regulatory approach, referred to as *uniform markup*, requires YPF to apply identical unit markups for each product type nationwide. The third policy alternative is *privatization*, which, in the context of our model, implies giving the firm a profit-maximizing mandate. We compare these policies against the current status quo in which the nationalized firm has complete discretion over pricing decisions.

Our analysis reveals that an optimal policy depends on how society trades off different dimensions, such as taxpayer costs, efficacy in curbing political price discrimination, impact on total consumer surplus, and overall welfare implications. We find a uniform pricing rule effectively reduces the influence of politics in pricing but is associated with higher social costs: it offsets half of the welfare gains generated by the nationalization and increases the burden on taxpayers, reducing YPF's profits by 4%. We find that a uniform markup rule improves allocative efficiency in comparison to uniform pricing—because of a closer alignment between prices and costs– but not in comparison to nationalization under discretion—since the government responds to the mandate by choosing higher markups on average and also because equilibrium effects are less pronounced. Interestingly, the uniform markup rule

[2]In the Argentinian context, representatives from both major political parties have advocated enacting price regulations for YPF by law to curtail regional pricing disparities.

is less effective than uniform pricing in preventing the government from favoring targeted households. The primitive that governs this result is the correlation between how much the government internalizes the welfare of a given household and how costly it is to serve it. In our application, targeted consumers are relatively cheaper to serve so the government can provide gasoline to those households at lower prices even under the rule. Finally, privatization is the best policy for the government's budget since it is equivalent to a profit-maximizing mandate. Still, it is the most detrimental for consumers and allocative efficiency due to market power exertion.

Contribution This paper adds to the existing literature by connecting the literature on interest groups with the literature on public vs private provision in an empirical application. In this regard, our contribution is twofold. First, we propose an empirical strategy to recover government preferences for allocative efficiency and redistribution in state-owned firms. Second, we examine the costs and benefits of different forms of price regulations that aim to limit the influence of interest groups on SOEs. Thus, the paper is connected with the literature on interest groups (Stigler, 1971; Peltzman, 1976; Laffont and Tirole, 1991; Dal Bó, 2006; Khwaja and Mian, 2005; Sapienza, 2004), literature on public vs. private provision (Krueger, 1990; Shleifer, 1998; La Porta and Lopez de Silanes, 1999).

This study also adds to the literature that compares public and private provision in empirical industrial organization (Illanes and Moshary, 2020; Seim and Waldfogel, 2013). Within this literature, this research is closely related to recent studies examining the effects of public provision in oligopoly markets such as Jiménez-Hernández and Seira (2021), Neilson et al. (2020), and Atal et al. (2021).

This paper showcases modern empirical IO tools to recover preferences underlying government decision-making. By doing this, we contribute to early attempts to recover preferences underlying government decision-making which focus on regulator (Timmins, 2002;

Kang and Silveira, 2021), and literature on conduct testing and estimation in empirical IO (Porter, 1983; Bresnahan, 1987; Nevo, 2001; Miller and Weinberg, 2017; Backus et al., 2021; Duarte et al., 2020). We add to that literature by allowing for heterogeneity in how different groups of consumers and firms are internalized (based on demographic and political characteristics) and by applying these tools to the estimation of the objective function of a state-owned firm.

Finally, the paper is connected to the literature on price discrimination. While researchers point out that firms can charge different prices based on non-economic attributes (Ayres and Siegelman, 1995; List, 2004; Goldsmith-Pinkham and Shue, 2023; Moshary et al., 2023), we show that the government can engage in price discrimination based on economic and political attributes.

Paper Organization The rest of the paper is organized as follows. Section 2 describes our data and the retail gasoline market before the nationalization of YPF. Section 3 presents descriptive evidence on the effects of nationalization on pricing and market outcomes. Section 4 introduces our model of demand and supply for gasoline. Section 5 discusses how the primitives of our model are identified; we describe how we estimate the model and present the results. In Section 6, we evaluate the effects of the nationalization by comparing it to what a profit-maximizing firm would have done. This exercise is also helpful in understanding the effects of privatization. Section discusses the effects of price rules, and Section 8 concludes.

3.2 Data and Institutional Background

3.2.1 The Retail Gasoline Market in Argentina

In this study, we examine the impact of the nationalization of YPF on the retail gasoline market in Argentina. In this market, non-commercial consumers purchase fuel at gasoline stations.[3] 90% of gasoline stations are contractually related to specific refineries (henceforth, vertically integrated). In contrast, the remaining 10% are independent (i.e., non- vertically-integrated).

When gasoline stations are vertically integrated with a refiner, the station displays the refiner's brand (i.e., Shell) and exclusively sells gasoline of that brand. Only 10% of gasoline stations are operated directly by refiners (company-operated stations), while most are owned and operated by third parties – usually individuals or small firms. When third parties operate branded gasoline stations, brands typically delegate the management to station owners but retain pricing decisions. [4] Station owners receive a commission for every liter of gasoline sold–between 10% and 20% of the retail price, depending on the brand and product type–plus additional payments based on performance. In contrast, non-vertically integrated stations acquire gasoline in the spot market and have complete control over pricing.

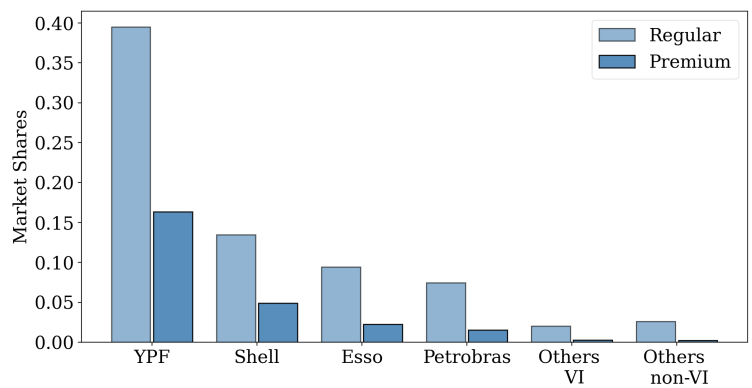
During our sample period, gasoline stations offered two types of gasoline: regular and premium. These products differ in their octane rating (RON), which affects engine performance. The law establishes that to market a product as premium gasoline, the product should have a RON rating above a certain threshold. Manufacturers usually recommend the use of premium gasoline for high-end cars. 70% of all premium gasoline is consumed by individuals in the fourth and fifth quintiles of the income distribution.

The retail gasoline market was concentrated among a limited number of firms during our sample period. YPF was the leading firm in regular and premium gasoline, accounting for

[3]We exclude commercial buyers as well as other types of fuel such as diesel or natural gas

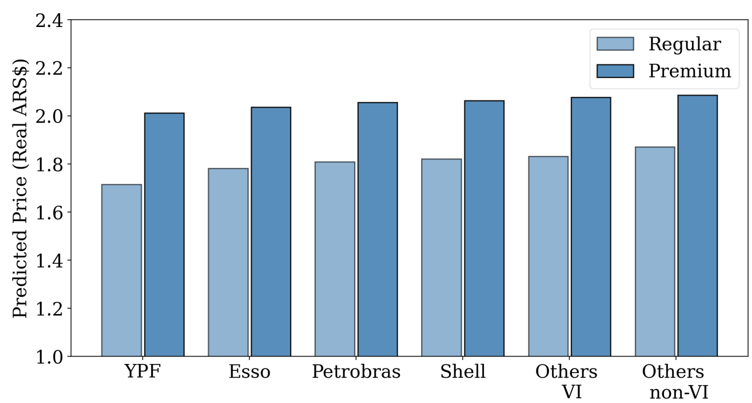
[4]For non-company-operated stations, two types of contracts were prevalent during our sample period. The first type of contract, used in all YPF stations, is called *consignacion*. In this type of contract, the refiner provides the gasoline to the gasoline station and has complete control over the price. The stationer receives a fixed commission for every liter sold. The second type of contract, used by the rest of the brands, is called *reventa*. In this contractual scheme, the refiner sets wholesale and retail prices for every product at every location daily. The difference between the list price and the wholesale price must be big enough to guarantee a given unit margin for the stationery. According to the contract, the stationer is mandated to purchase the product at the wholesale price. However, the stationer is not legally obligated to charge the list price and can deviate from that based on market conditions.

55% of all gasoline sales. YPF was followed by international brands such as Shell, Esso, and Petrobras. These four brands combined controlled 95% of all the gasoline sold. The dominance of YPF in both products can be attributed to a combination of having a more extensive network of gasoline stations and providing low-priced products. Figures 3.1 and 3.2 summarize each brand's market shares and average prices before the nationalization.



Note: This figure shows the market shares of each firm in the calendar year before the nationalization.

Figure 3.1. Market shares by firm and product type



Note: This figure illustrates predicted prices by brand and product type in the calendar year before the nationalization (Jan-2011 to Dec-2011), expressed in CPI-adjusted pesos. Prices are projected into brand indicator variables and market-time fixed effects using separate regressions for regular and premium gasoline. The displayed plot represents the coefficient of the brand indicator variables.

Figure 3.2. Pricing by firm and product type

3.2.2 Data

This subsection describes the data used in this paper.

Gasoline stations data The first data source is a gasoline station dataset. Since 2008, gasoline stations have been obligated to report the volumes of fuel sold to the Secretariat of Energy, categorized by fuel type and customer type (Resolucion S.E. 1104/2004). They must also report the average selling prices with and without taxes and the current pump prices on the last day of the month. The database also includes information on the gasoline station address, brand, and identity of its owner (name and tax code). Our sample covers the period from January 2010 to December 2015.

Refineries and terminals data The refineries and terminals dataset includes monthly observations of prices and quantities of gasoline sold by refineries, aggregated by type of client (such as own stations or third parties) and regions, as well as information on refineries and terminal's addresses. This dataset was obtained from the Argentinian Secretary of Energy and covers the same period as the gasoline stations dataset.

Census and Expenditure data To identify the location of households and their main demographic characteristics, we use census data from the 2010 Census. We expanded this data by combining it with expenditure surveys obtained from the Argentina Census and Statistics Bureau (INDEC), which covered the period from August 2017 to July 2018. The expenditure surveys provide information on the spending habits of households, including their spending on gasoline and whether or not they have cars.

Electoral data To evaluate the relationship between pricing and electoral outcomes, we utilize data from the 2011 presidential and legislative elections provided by the National

Electoral Directorate.

3.2.3 Market Definition

We define geographic markets as sets of gasoline stations and census blocks. Markets are mutually exclusive sets, meaning each gasoline station (and each census block) belongs to only one market. By doing this, we guarantee that gasoline stations that share customers belong to the same market.

We define markets using the following algorithm.

1. For each census block, consider stations 10 km from its centroid.
2. Combine census blocks with at least one common station into a single cluster.
3. Combine clusters with at least one station in common until all clusters are mutually exclusive sets of stations and census blocks.
4. Exclude markets in which YPF is a monopolist.[5]

After running the algorithm, we define 272 markets distributed across 23 provinces. Tables 3.1 present summary statistics of markets. See Figure C.5 in the appendix for an example of all the markets in the province of Mendoza. See Table C.1 in the appendix for additional summary statistics.

[5] We will not be able to identify the effects of the nationalization in markets where YPF is a monopolist. See Section 3.5.3 for a discussion.

	All	**Sample**
# Markets	404	272
# Stations		
p25	1	2
p50	2	4
p75	5	6
p90	9	11
Total	2,787	2,655
Price		
p25	1.72	1.75
p50	1.76	1.78
p75	1.81	1.84
p90	1.87	1.89
Volume (Th. m3)		
p25	80	175
p50	185	325
p75	461	759
p90	1258	1822
Total	407,776	397,548

Note: Note: This table presents the summary statistics of the markets created using the algorithm described in the text. The first column describes all the markets. The second column describes our estimation sample.

Table 3.1. Summary statistics - Sample

3.2.4 The Nationalization of YPF

The Argentinian government took control of YPF in April 2012, and two months later, an expropriation law was passed to make the intervention permanent. The expropriation law was approved by a broad majority in both chambers of Congress, with the support of most opposition members. As part of the expropriation law, Argentina acquired 51% of YPF's shares. These shares were distributed between the federal government, which got 26% of the shares, and a group of oil-producing provinces that received 24.99% of the shares. We refer to these provinces as the *shareholder provinces* or *provinces with political ties* or *oil-producing provinces*.[6] The remaining 49% of the shares remained in the hands of private investors.

As we document in the next section, the nationalization was followed by a change in relative prices across geographic markets and products. Since YPF was nationalized, different market participants have suggested the influence of politics in pricing. Below, we present illustrative quotes from different market participants:

> ”The city of Buenos Aires has lower prices than [the Province of] Mendoza not because of economic matters but for political decisions” Oscar Diaz, Chamber of Gas Stations President. July 2015.

> ”[The province of] Misiones asked [YPF authorities] to pay the same gasoline prices that are paid in the rest of Argentina.” Misiones Province Governor, March 2022

In the next section, we provide descriptive evidence of the connection between pricing and politics after the nationalization.

[6] According to the Argentine Constitution, provinces own natural resources and are entitled to both concede exploitation rights and receive royalties from exploitation. Thus, they have a vested interest in YPF's operations.

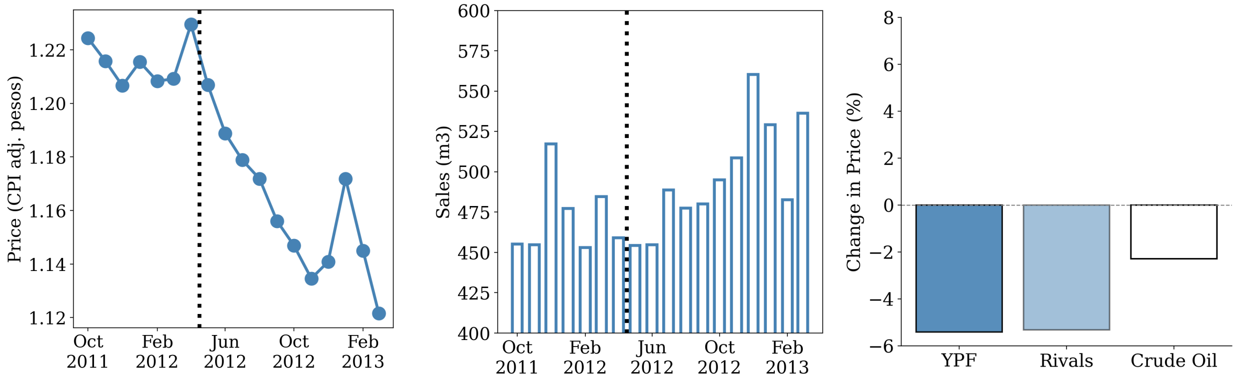
3.3 Descriptive Evidence

This section provides descriptive evidence of the impact of YPF's nationalization on gasoline prices. This will also motivate the modeling assumptions we present in the subsequent section. The evidence suggests that the government sets prices differently than a profit-maximizing firm in three dimensions. Firstly, it exerts less market power, charging lower prices on average. Secondly, it engages in less price discrimination *based on economic factors*. Lastly, it engages in price discrimination *based on political factors*.

3.3.1 Fact 1: Prices Dropped and Gasoline Consumption Increased

Figure 3.3 displays the trends in gasoline prices and sales pre and post-nationalization. In comparison to the last month before the nationalization, gasoline prices dropped by 5%, and gasoline sales increased by 4%. Panel c shows that price drops were similar in magnitude for both YPF and rival firms and that price changes were not explained by a decline in crude oil prices.[7] The overall surge in sales was primarily attributed to the increase in consumption of YPF's regular gasoline. This fact suggests that the nationalization was associated with lower gasoline prices for YPF and generated an expansion in the market. Refer to Figure C.9 in the appendix for additional descriptive statistics regarding gasoline sales.

[7] Gasoline prices dropped more than crude oil prices. This observation holds when compared to the month just before nationalization and the two years leading up to it. Further details are available in Figure C.8 in the appendix.



Note: Note: Panels a and b display the evolution of prices (panel a) and gasoline sales (panel b) for the period Oct-2011 to Feb-2013. The dotted line represents the date of the nationalization. Prices are expressed in CPI-adjusted pesos and do not include federal taxes. Panel c compares the change in gasoline prices and crude oil prices. It compares the post-nationalization period (May 2012 to February 2013) vs. the last month before the nationalization (April 2012). Refer to section C.2 for additional descriptive statistics.

Figure 3.3. Evolution of gasoline prices and sales

3.3.2 Fact 2: Larger Price Drops for More Inelastic Products

A profit-maximizing firm engages in price discrimination by charging higher prices to consumers with a higher willingness to pay (i.e., more inelastic consumers). Three patterns in the data indicate that price reductions were more significant in more inelastic products after the nationalization, suggesting the government engaged in less price discrimination based on economic attributes. First, the price of regular gasoline dropped relatively more in middle and high-income neighborhoods compared to low-income neighborhoods. Second, YPF reduced the price of premium gasoline relatively more than regular gasoline. Third, YPF gasoline prices experienced larger drops in markets in which YPF had higher market shares. We explain these three patterns in turn.

Price drops by location's income We examine whether YPF changed prices differently among different locations after the nationalization based on the income level of the population living near the gasoline station's location. In our setting, higher-income consumers are shown to be more inelastic.[8]

We regress YPF gasoline prices on whether the station is in a low, middle, or high-income neighborhood and interactions between the post-nationalization period and the station's associated income level.

$$price_{i,t} = \alpha_{\text{inc}(i)} + \sum_{j \in \{\text{ M, H}\}} \beta_j \times post_t \times \mathbf{1}\{\text{inc}(i) = j\} + \tau_{\text{prov}(i)} + \gamma_t \tag{3.1}$$

In the equation above, $\alpha_{\text{income}(i)}$ are fixed effects for the income of the median household located in the same census block as the station; $\tau_{\text{prov}(i)}$ are province fixed-effects (capturing differences in both transportation, and costs among provinces), and γ_t are time fixed-effects; β_j is the coefficient associated with the interaction between the station's neighborhood income and a post-nationalization indicator variable. Figure 3.4 (a) presents the estimates of $\alpha_{\text{inc}(i)}$ and β_j, the coefficients of interest. Stations located in low-income neighborhoods are the control group. We refer the reader to Appendix C.2.2 for regression tables and alternative specifications.

The results indicate that, before the nationalization, YPF charged 2% higher gasoline prices in middle and high-income areas thant in lower-income areas. Under the assumption that marginal costs are the same within a province, this suggests that YPF charged higher markups to more inelastic consumers before the nationalization. However, after the nationalization, the price gaps between zones with different income levels within a province became more subtle, suggesting YPF is charging relatively lower markups to more inelastic consumers.

[8] This is confirmed by our demand estimates (see Table 3.2) and is consistent with demand estimates in other countries (Houde, 2012; Wadud et al., 2010). Furthermore, expenditure survey data shows that higher-income households pay higher gasoline prices, controlling for location and product type (See Appendix C.1.1). Also, as we show next, pre-nationalization prices were higher in high-income locations, controlling for province fixed-effects.

Price drops by product quality We study if YPF changed relative prices between regular and premium gasoline after the nationalization. Premium gasoline is a more expensive product (20% more than regular gasoline in the pre-nationalization period), and according to expenditure survey data, it is consumed almost exclusively by middle-income and high-income households. So, we expect premium gasoline to have more inelastic demand.[9] We regress YPF prices on an indicator of whether the product is premium gasoline (premium_i) and an interaction between an indicator of whether the product is premium gasoline and an indicator of the post-nationalization period. We include time and station fixed effects ($\tau_{\text{station}(i)}$).

$$price_{i,t} = \alpha \times \text{premium}_i + \beta \times \text{post}_t \times \text{premium}_i + \tau_{\text{station}(i)} + \gamma_t \tag{3.2}$$

α and β are the coefficients of interest. Figure 3.4 (b) presents a visualization of the results. We refer the reader to Appendix C.2.2 for regression tables. Before the nationalization, YPF's premium gasoline was 22% more expensive than regular gasoline. After the nationalization, the price difference decreased to approximately 10%. Under the assumption that there were no changes in the relative costs between producing regular and premium gasoline after the nationalization, this result also suggests that YPF reduced prices of products with a more inelastic demand relatively more.

Price drops by market concentration We test if YPF changed relative prices between areas with different market shares after the nationalization. Assuming demand is more inelastic in markets with larger YPF market shares (because consumers have fewer options to switch to), a profit-maximizing firm would charge relatively higher prices in more concentrated markets. We regress YPF prices on a variable capturing YPF's market share in that market before the nationalization ($\text{share ypf}_{(i)}^{\text{pre-nac}}$), and an interaction between

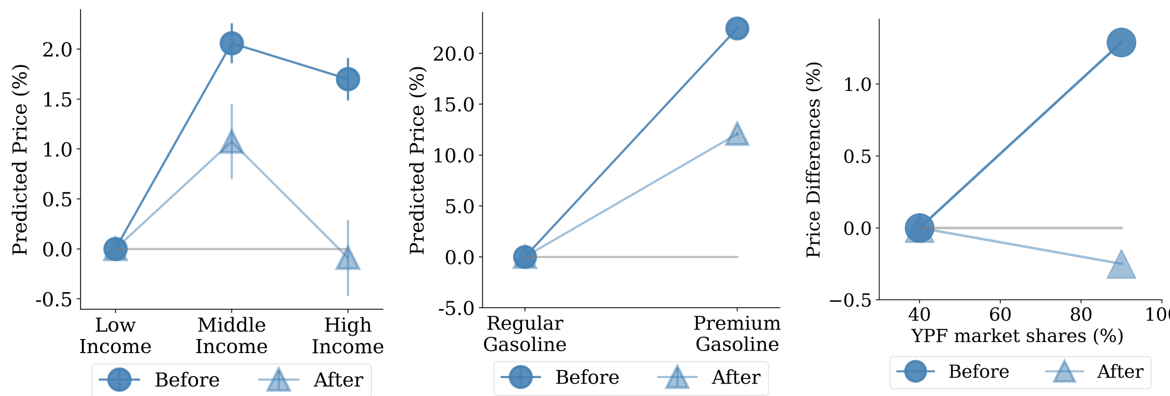
[9] We confirm this hypothesis with our demand estimates. See Table C.8 in Appendix C.3.1

YPF's market share in that market before the nationalization and an indicator of the post-nationalization period. We included province-fixed effects to capture cost differences among different provinces and time-fixed effects.

$$price_{i,t} = \alpha \times \text{share ypf}^{\text{pre-nac}}_{(i)} + \beta \times \text{post}_t \times \text{share ypf}^{\text{pre-nac}}_{(i)} + \tau_{\text{province}(i)} + \gamma_t \tag{3.3}$$

In the equation above, α and β are the coefficients of interest. Figure 3.4 (c) presents a visualization of the results. We refer the reader to Appendix C.2.2 for regression tables and alternative specifications. This exercise reveals that, before nationalization, YPF charged higher prices in markets with higher market share. However, this pattern disappeared after the nationalization. Under the assumption that marginal cost is the same within a province, this suggests a correlation between markups and YPF market shares before the nationalization. Under the assumption that marginal cost didn't decrease relatively more in places where YPF had more market shares, this suggests that nationalization was associated with a reduction in markups in markets where YPF had more market share.[10] These three facts suggest that YPF exerted less *economic* price discrimination after the nationalization.

[10]Regressing prices on market shares will typically suffer from endogeneity problems, so we cannot give a causal interpretation to the coefficients of this regression. The exercise aims to show that prices decrease relatively more after the nationalization in markets where we expect YPF to have more market power. In Appendix C.2.3, we show that this result holds under alternative specifications.

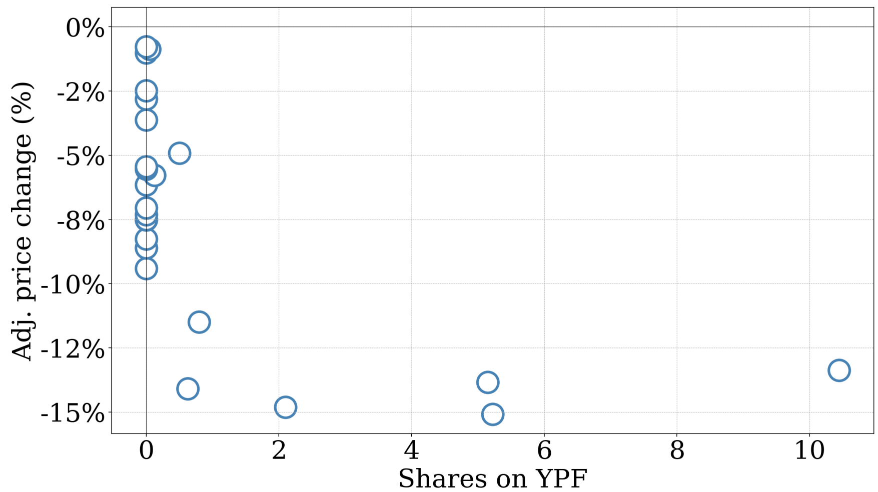


Note: *Note:* This graph displays the results of regressions 3.1, 3.2, and 3.3. Refer to Table C.3 on Appendix C.2.2 for regression tables. Panel (a) shows the correlation between YPF's prices and the station's location income level pre- and post-nationalization, controlling for time and province fixed-effects (equation (3.1)). The dark blue line (*before*) presents the value of $\alpha_{\text{inc}(i)}$ and the light blue line (*after*) presents the value of $\alpha_{\text{inc}(i)} + \beta_j$. The station's location income is defined as the median income of households within the census block of the station's location. Stations in low-income neighborhoods are the control group, so its coefficient is normalized to zero in the plot. We use data for all product qualities, but results are similar when restricting the sample to regular gasoline. See Appendix C.2.2. Panel (b) shows predicted prices by product type in the pre and post-nationalization periods, controlling for station and time fixed-effects (equation (3.2)). The dark blue line (*before*) presents the value of α, and the light blue line (*after*) presents the value of $\alpha + \beta$. Panel (c) shows the correlation between YPF's market shares pre-nationalization and prices pre- and post-nationalization, controlling for province fixed effects (equation (3.3)). For illustration purposes, the regression line plot spans from the 10th to the 90th percentiles of YPF's observed market share distribution. The dark blue line (*before*) presents a regression line for α, and the light blue line (*after*) presents a regression line for $\alpha + \beta$.

Figure 3.4. Regressions results: visualization

3.3.3 Fact 3: Larger Price Drops in Politically Connected Provinces

The nationalization was associated with lower prices in provinces that had political connections to the firm. As part of the expropriation law, Argentina acquired 51% of YPF's shares. These shares were distributed between the federal government, which kept 26% of the shares, and a group of oil-producing provinces that received 24.99% of the shares. We found that gasoline prices dropped 7% percentage points more in the provinces that acquired shares post-nationalization. Figure 3.5 illustrates the relation between province's shares on YPF and price drops (adjusted by changes in crude oil prices).



Note: *Note:* This graph illustrates the change in YPF's prices as a function of provincial share ownership in YPF. We compare the average prices in the pre-nationalization period vs. those in the post-nationalization period. Prices are adjusted for the evolution of crude oil prices and exclude taxes. The pre-nationalization period spans from January 2010 to March 2012, while the post-nationalization period covers May 2012 to February 2013.

Figure 3.5. YPF's price changes as a function of provincial share ownership: before vs. after

Following Peltzman (1976), we provide a simple rationale for the heterogeneity in prices between shareholder and non-shareholder provinces. From a politician's perspective, lowering gasoline prices has benefits and costs. On the one hand, lower gasoline prices are associated with better electoral outcomes. Indeed, recent empirical evidence using data from different countries shows that higher gasoline prices are associated with a lower probability of incumbents being re-elected (Arezki et al., 2022). On the other hand, lower gasoline prices translate into lower revenues for the federal government and shareholder provinces through YPF's profits. This reduces resources available for public goods and transfers, potentially affecting re-election chances. Lower YPF prices also lead to lower industry revenues, meaning lower opportunities for financing political campaigns.

However, different politicians will have different preferences for the distribution of gasoline prices across the country. While the federal government internalizes the political benefits and cost of lowering prices in all provinces, governors only internalize the political benefits of reducing prices in their provinces but not elsewhere. Consequently, each governor typically prefers lower prices for their province and higher prices for others. Under the assumption that having shares in the firm gives governors influence over pricing decisions, we expect to observe relatively lower prices in shareholder provinces. This intuition is consistent with the pricing patterns we observe in the data.

Robustness Checks We performed a set of checks to rule out the possibility that province-level costs or demand shocks explain the heterogeneity in price changes between shareholder and non-shareholder provinces.

First, we explore the possibility that efficiencies in crude oil production might be driving the relative price changes. We find evidence contrary to this hypothesis. Crude oil needs to be refined before it can be sold as gasoline, so any efficiency or inefficiency in crude oil production itself would translate into lower gasoline costs for all provinces and not exclusively for shareholder provinces

Additionally, we checked if the change in relative prices is explained by changes in YPF transportation costs that were contemporaneous with the nationalization. We found evidence contrary to this hypothesis. First, stations in shareholder provinces vary widely in their distance from refineries. While some stations in shareholder provinces are close to a refinery, others are far away. Second, there is almost no correlation between the distance to a refinery and the effects of nationalization (see Appendix C.2.4). Considering these facts, we rule out the possibility that a reduction in transportation costs contemporaneous with the nationalization can explain lower prices in shareholder provinces.

Third, we compared the evolution of YPF gasoline sales in oil-producing and non-oil-producing provinces to rule out the possibility that lower prices in shareholder provinces are explained by lower demand for gasoline in shareholder provinces. We found that gasoline sales increase slightly more in shareholder provinces than in the rest of the country (See Figure C.13 in the appendix).

Fourth, we use a difference-in-differences design to rule out the possibility that price drops in shareholder provinces are explained by unobserved cost or demand shocks that affect all stations in each province. In particular, we compare prices of rivals' stations (i.e., Shell stations) located near a YPF station with prices of rivals' stations of the same brand located far away from a YPF station in a similar province. If price differences observed after the nationalization were caused by shocks that affect all stations in a given province, prices of rivals located near a YPF station should trend similarly to prices of rivals that are far away. However, if the price changes were driven by changes in YPF's conduct, we should observe more pronounced price reductions in rivals close to a YPF station compared to those located far away.[11] We find that rivals' stations located near a YPF station in shareholder provinces experienced a 7% larger price drop than rival stations located 10km away or further from a YPF station. Moreover, we observe that price trends were similar before the nationalization. We refer the reader to Appendix subsection C.2.5 for details.

Finally, we examine whether the observed price reduction in oil-producing provinces stemmed from a national-level uniform pricing policy implemented after the nationalization. We found evidence contrary to this hypothesis. In particular, we found that prices were more dispersed after the nationalization and not more uniform. The price differences between shareholder and non-shareholder provinces explain the bulk of the additional dispersion.

Overall, provinces that acquired YPF's stocks experienced greater price reductions. This finding is consistent with cross-subsidization across consumers of different regions driven by

[11]The identifying assumption is that if the nationalization did not affect YPF's conduct and all price changes were explained by changes in the province's specific demand or cost shocks, the evolution of prices of a rival station located near a YPF station after the nationalization should be similar to the evolution of a rival station of the same brand located in the same province but less exposed to YPF competition

political connections between the SOE and provincial governors.

3.3.4 Discussion

This section provides evidence suggesting that YPF's pricing strategy shifted post-nationalization. First, we document that the nationalization was associated with lower prices and increased YPF sales. This is consistent with the state-owned firm exerting less market power than a profit-maximizing firm and benefiting consumers. Second, we document that price discrimination patterns changed after the nationalization. On the one hand, the evidence suggests that YPF is exerting less *economic price discrimination*. This means that YPF does not charge higher prices to consumers with a greater willingness to pay, seemingly favoring middle and high-income consumers. On the other hand, there is evidence that suggests YPF engaged in *political price discrimination*, setting prices based on governors' political affiliations with the SOE in different provinces.

Price changes are consistent with a change in the objective function of YPF after the nationalization. When shifting from privately owned to state-owned, the firm might have started internalizing the effects of prices on other participants' welfare, such as consumers and firms. It might also internalize the impact of prices on the political outcomes of the federal government and governors of shareholder provinces.

However, other factors could also have influenced pricing. Our descriptive analysis provides evidence against province-specific cost or demand-side explanations. We also provide evidence against YPF-specific transportation costs' explanations. Nevertheless, we cannot rule out more involved demand or cost-side explanations. For instance, prices might have changed because consumers changed their preferences for YPF products after the nationalization. Moreover, prices might have changed due to shifts in gasoline costs specific to some areas within a province.

To fully disentangle between *objective function*, *cost side*, and *demand side* explanations, we need to compare the prices that YPF charged after the nationalization with the prices that *profit-maximizing* YPF would have charged under the same demand and supply conditions on every gasoline station and product. In the following section, we introduce a structural model of supply and demand for gasoline that allows us to perform this comparison.

3.4 A Model of the Retail Gasoline Market

This section describes a model of demand and supply for gasoline. On the supply side, firms choose gasoline prices for all gasoline stations under their control. On the demand side, consumers decide where to buy gasoline. Gasoline products are differentiated based on location (consumers dislike traveling to get gasoline), brand, product-specific, and station-specific characteristics. We divide time into two periods: *before the nationalization*, where all firms are profit-maximizers, and *after the nationalization*, where YPF maximizes a flexible objective function, and rival firms maximize profits.

3.4.1 Demand Side

Each consumer living in a geographic market m can choose among a set of $j = 1, \dots J_m$ gasoline products or select the outside option (which means using an alternative mode of transportation). Any given product j is defined by its location (the geographic coordinates of the gasoline station where that product is sold) and octane rating. If the octane rating is below 97 RON, it is marketed as regular gasoline; If it is on or above 95 RON, it is marketed as premium gasoline. Consumers are heterogeneous in two dimensions. The first dimension is their location (defined by the centroid of the census block where they live), and the second is their income level (low-income, middle-income, or high-income). The indirect utility of buying product j for consumer i is given by:

$$u_{ijt} = \underbrace{\alpha_i p_{jt} + \gamma D(l_i, l_j) + \beta_i \mathbf{X}_{j,t} + \xi_j + \xi_t + \Delta\xi_{jt}}_{v_{ijt}} + \epsilon_{ijt} \tag{3.4}$$

where p_{jt} is the retail price of product j at month t, $D(l_i, l_j)$ is the distance between consumer's location and station's location and $\mathbf{X}_{j,t}$ is a vector including product characteristics. ξ_j is an index of station-product attributes that are constant across time (such as station characteristics and brand), and ξ_t captures trends in valuation for all inside goods in each month. The indirect utility function's specification includes time-varying product attributes observed by consumers but unobserved by the econometrician: $\Delta\xi_{jt}$. This parameter captures product-specific deviations from both ξ_j and ξ_t (such as changes in brand valuation at specific periods or changes in station characteristics that are unobservable for the econometrician). In this model, consumers have heterogeneous preferences for gasoline products. First, consumers rank products differently based on the distance between their location and the gasoline station's location (captured by $\gamma \times D(l_i, l_j)$). Second, consumers are more or less sensitive to high prices based on their income (captured by α_i). Third, different consumers have different preferences for buying gasoline vs. choosing the outside good (captured by $\beta_i \mathbf{X}_{j,t}$). Finally, we assume consumers have idiosyncratic preferences for products ϵ_{ijt} that follow an i.i.d. type 1 extreme value distribution. The utility of choosing the outside option is normalized to zero.

According to the model, market shares for product j at time t are given by

$$s_{jt} = \sum_{i \in I_m} \frac{exp(v_{ijt})}{1 + \sum_{k \in J_m} exp(v_{ikt})} w_i \tag{3.5}$$

where I_m refers to the set of households living in market m, and wi captures the weight of each household on that market.

3.4.2 Supply Side

Firms simultaneously choose prices for each product under their control, for each market and month m. By a firm, we mean a refinery controlling the prices of all gasoline stations under the refinery's brand. So, all SHELL stations in a given market constitute a firm, and all ESSO stations in that market are part of a different firm [12]. We define products as combinations of geographic location and product type (regular or premium gasoline). For instance, premium gasoline at Shell station 'A' is a product, and regular gasoline at that station is a different product.

Product j at time t has a marginal cost mc_{jt}. For stations that are vertically integrated with a refinery, which constitute 97% of the market, this represents the cost of buying crude oil, refining and mixing it with other components to obtain gasoline, transporting gasoline to the gasoline station at which product j is sold, and paying all type of marketing costs (including fees to station owners). For non-vertically integrated firms (unbranded stations and small brands), this is the cost of buying gasoline at a terminal, transporting it to the gasoline station, and marketing it.

We divide our sample into two periods: before and after the nationalization. In the pre-period, we assume all firms (including YPF) simultaneously choose prices for each product under their control to maximize profits.

Assumption 1 *Competition in the pre-nationalization period*

In each geographical market and month and conditional on rivals' prices $\boldsymbol{p}_{-f}$, firm f chooses a set of prices $\boldsymbol{p}_f$ such that:

$$\max_{\boldsymbol{p}_f} \Pi(\boldsymbol{p}_f, \boldsymbol{p}_{-f}) \equiv \max_{\boldsymbol{p}_f} \sum_{j \in \mathcal{J}_f^m} (p_j - mc_j)\, Q_j \left(\boldsymbol{p}_f, \boldsymbol{p}_{-f}\right)$$

[12]Sometimes, a set of unbranded stations is controlled by the same individual. In those cases, we define that set of unbranded stations as a firm

In the post-period, we assume all firms except YPF choose prices simultaneously. While all firms but YPF maximize profits (as in the pre-nationalization period), we assume YPF maximizes its objective function $W(\mathbf{p})$, which is unobservable for the econometrician.

Assumption 2 *Competition in the post-nationalization period*

On each geographical market and month and conditional on rivals' prices $\boldsymbol{p}_{-YPF}$, firm YPF choose a set of prices $\boldsymbol{p}_f$ such that:

$$\max_{\boldsymbol{p}_{YPF}} W(\boldsymbol{p}_{YPF}, \boldsymbol{p}_{-YPF}) \tag{3.6}$$

and for all firms except YPF, the problem of firm f on market m is:

$$\max_{\boldsymbol{p}_f} \Pi(\boldsymbol{p}_f, \boldsymbol{p}_{-f}) \tag{3.7}$$

Equation 3.8 presents our benchmark specification for YPF's objective function $W(p)$. The first term captures the effect that YPF pricing has on its profits. The second group of terms captures the effect that YPF pricing has on consumers. To do that, we divide the universe of consumers into G groups $g = 1, \ldots, G$. A consumer group is a combination of a province and an income level. Finally, the consumer surplus of different consumer groups enters as arguments of $W(p)$, weighted by λ_g parameters. By including different λ_g parameters, the model is flexible enough to capture that the consumer surplus of different groups might be weighted differently. The third group of terms captures the effect that YPF pricing has on rival brands' profits.

Assumption 3 *YPF's objective function specification is*

$$W(\boldsymbol{p}) = \underbrace{\Pi(\boldsymbol{p})}_{\textit{YPF's own profits}} + \sum_{g=1}^{G} \lambda_g \times \underbrace{CS_g(\boldsymbol{p})}_{\textit{group } g \textit{ consumer surplus}} + \sum_{f=1}^{F} \kappa_f \times \underbrace{\Pi_f(\boldsymbol{p})}_{\textit{brand } f \textit{ profits}} \tag{3.8}$$

3.4.3 Discussion

We conclude this section by discussing the main simplifying assumptions we introduce in the model. On the demand side, we assume that consumers prefer gasoline stations closer to their households over those farther away. In practice, a proportion of consumers regularly commute to work (or do any other activity), so they might be indifferent between purchasing gasoline at a station that is one block away from their home and a station that is one block away from work (Houde, 2012). This assumption might be problematic for big cities (where consumers might live far away from their work). We address this issue by removing from our sample the three main metropolitan areas in Argentina (Buenos Aires, Cordoba, and Rosario). Assessing the effect of the nationalization in those areas is left for future work.

In terms of the vertical structure of the market, we made two assumptions. First, we assume that refiners affect market outcomes only through the prices of their station network. This assumption might be problematic if refineries could affect market outcomes significantly through the gasoline they sell to independent and unbranded stations. In the Argentina gasoline market, 97% of gasoline is sold via vertically integrated stations. Second, we assume that station owners cannot deviate from the retail prices set by refineries. While this is true for YPF stations and company-operated stations of other brands, station owners non-affiliated with YPF are usually contractually able to deviate from list prices. However, such deviations are not standard and are penalized by refineries. This was confirmed in conversations with station owners and executives of gasoline companies.

The second simplification on the supply side is that firms compete Bertrand-Nash before the nationalization (Assumption 1). We impose this assumption to make use of all the pre-nationalization period data. Absent this assumption, we require an alternative set of instruments to identify YPF's conduct after the nationalization.

The third simplification is that YPF's objective function is linear in an array of consumer surplus measures for different groups of consumers, YPF's profits, and rivals' profits. The arguments of the objective function we choose have two benefits. First, they allow us to capture most of the patterns we observe in the data. Introducing heterogeneity in consumer surplus over provinces (or province type)allows us to capture the fact that price reductions might be larger in oil-producing than in non-oil-producing provinces. Allowing heterogeneity in consumer surplus according to consumers' income allows us to capture different pricing patterns for regular and premium gasoline and different pricing patterns for different geographic locations within a province (or a group of provinces). Moreover, this specification can generate the type of economic and political price discrimination patterns that we observe in the data. In our model, economic and political price discrimination patterns are outcomes generated by the government's preference for different groups of consumers.

Also, the objective function specification encompasses objective functions that prior theoretical research used to characterize mixed oligopolies. These include total surplus maximization, profit maximization, or different weights for consumer surplus and rival's profits.

The last simplification is that the game is static. A potential concern is that the nationalization might induce gasoline stations to exit the market, making the entry/exit margin relevant for the analysis. This simplification is based on the fact that the number of gasoline stations remained unchanged after the nationalization.

3.5 Estimation, Identification and Results

3.5.1 Demand Side: Estimation and Identification

Estimation We estimate the demand primitives using the generalized method of moments. We use different sets of moment conditions following Berry et al. (1995) and Petrin (2002). The first set of moment conditions captures the assumption that unobserved disturbances on product valuations are uncorrelated with observed demand-side variables (except for prices) ($\mathbf{X^d}$) and demand-side instruments ($\mathbf{Z^d}$), such that:

$$E\left[\Delta\xi_{jt}|\mathbf{X^d},\mathbf{Z^d}\right]=0$$

We supplement standard BLP-type moment conditions with micro-moments (Petrin, 2002). First, we match the average probability of consuming gasoline, conditional on the income level generated by the model, with what is observed in the expenditure survey.

$$E[\text{i purchase gasoline}|\text{income}_i = I] \quad \forall I$$

Second, we match the probability of consuming premium gasoline conditional on income level:

$$E[\text{i purchase premium gasoline}|\text{income}_i = I] \quad \forall I$$

The two sets of moment conditions entering the GMM objective function are $\mathbf{G}_1(\theta)$ (the BLP type moments) and $\mathbf{G}_2(\theta)$ the micro-moments associated with the expenditure survey data. Thus,

$$E\left[\mathbf{G}\left(\boldsymbol{\theta}_0\right)\right]=E\begin{bmatrix}\mathbf{G}_1\left(\boldsymbol{\theta}_0\right)\\ \mathbf{G}_2\left(\boldsymbol{\theta}_0\right)\end{bmatrix}=0$$

The GMM estimator is given by

$$\hat{\theta}^{GMM}=\arg\min_{\theta\in\Theta}\hat{\mathbf{G}}(\theta)'W\hat{\mathbf{G}}(\theta)$$

where $\hat{\mathbf{G}}(\theta)$ is the sample analog of $\mathbf{G}(\theta)$ and W is the weighting matrix. We implement the standard two-step procedure for GMM estimation. In the first step, we set $W=(\frac{Z'Z}{N})^{-1}$. In the second step, W is updated according to $W=S^{-1}$, where $S=\frac{1}{N}\sum_{j,t}G_{jt}G'_{jt}$.

Identification Three sets of parameters exist on the demand side: price sensitivity (α), demographic-specific valuation for product characteristics (β), and travel cost parameters γ. Identifying price sensitivity α requires instrumental variables correlated with prices yet conditionally independent of unobserved disturbances on product valuations $\Delta\xi_{jt}$. We exploit the variation in gasoline tax rates that occurred after the nationalization as an instrument to identify α.[13] The federal government and the province of Cordoba both introduced or modified gasoline taxes between 2013 and 2017, resulting in variations in prices. This variation is arguably uncorrelated with unobserved disturbances at the gasoline station level.

Identification of demographic-specific valuation for product characteristics β is achieved through micro-moments that match the probabilities of purchasing different products by distinct demographic groups. Specifically, micro-moments that match the probability of buying gasoline conditional on the household's income level enable us to determine how individuals from different income groups value goods inside the market compared to the outside option. Likewise, micro-moments that match the probability of purchasing premium gasoline conditional on the household's income level allow us to ascertain how individuals from different income groups balance quality and prices.

Finally, the travel cost parameter γ is identified by analyzing observed substitution patterns triggered by price changes or the entry (exit) of stations in the market. Consider a scenario where travel costs are zero ($\gamma = 0$) and a particular station raises its prices. In that situation, we would observe that the substitution toward geographically proximate stations closely resembles the substitution toward more distant stations. Conversely, if travel costs are high, we should observe substitution concentrated around geographically close stations following a price increase, with minimal impact on remote stations.

[13]Tax changes happened after the end of the sample period we use to assess the effects of the nationalization. To exploit this variation, we use a more extended sample spanning from 2010 to 2017.

3.5.2 Demand Side: Results

Results for demand estimation are presented in Table 3.2. The coefficients exhibit the anticipated signs. The interactions between price and household income indicate that higher-income consumers are less price-elastic. As expected, consumers dislike traveling to get gasoline. Our estimates suggest that a lower-income consumer is willing to travel an additional kilometer to access more affordable gasoline of the same quality, provided the discount exceeds 1.2%

	coeff	**s.e.**
price (α)	-0.69	(0.17)
distance (γ)	-1.54	(0.74)
Demographic Interactions (β)		
constant $\times$ M	0.27	(0.77)
constant $\times$ L	25.39	(2.94)
price $\times$ M	-1.73	(0.43)
price $\times$ L	-12.27	(1.52)
Own-price Elasticity (p50)	-3.52	
Median Market Elasticity	-0.53	
1 km cost (% of P) for L	1.2%	
1 km cost (% of P) for M	6.4%	
1 km cost (% of P) for H	22.4%	
Number of markets	26776	

All specifications include time and station-product fixed-effects.

Note: Note: The above table presents estimates and standard error for demand parameters corresponding to (3.4). The omitted category is high-income households. Time and station-product fixed effects are included. Observations are weighted by market size. Standard errors are clustered by region. Our sample goes from January 2010 to December 2017.

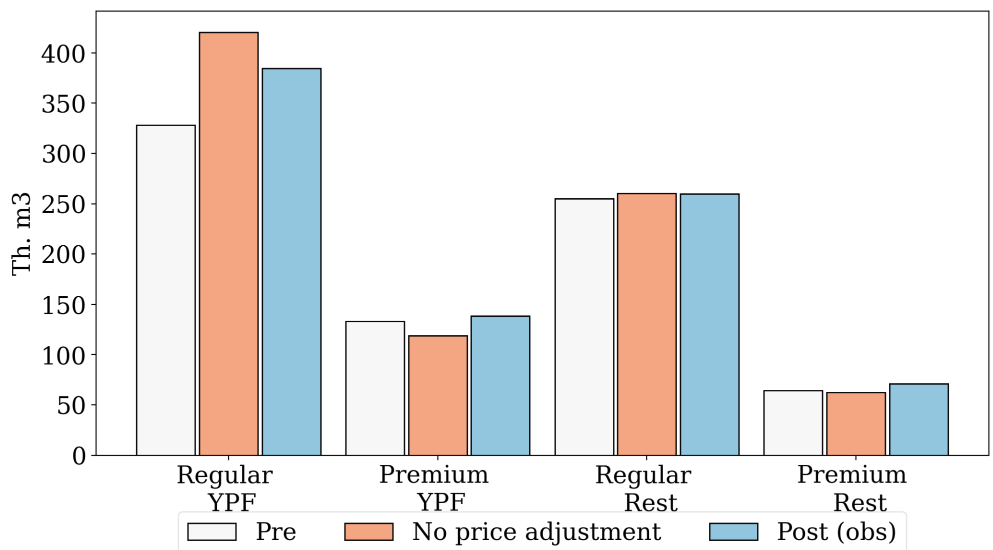
Table 3.2. Baseline demand estimates

Our estimates can capture expected substitution patterns across stations. To characterize the substitution patterns indicated by our demand estimates, we regress the estimated cross-price elasticities for each pair of products k and l within the same market on whether both products are of the same quality (both regular or both premium gasoline); whether both products are of the same brand; whether both products are on the same station; and whether l is the closest rival of k, the second closest rival of k, etc. First, greater substitution is linked to nearby stations, while substitution becomes nearly negligible for more distant stations. Additionally, substitution is more pronounced among stations of the same brand, products within the same station, and products of the same quality (for instance, premium Shell is a closer substitute to premium ESSO than regular ESSO). We refer the reader to Table C.10 in the appendix for regression tables.

Own-price elasticities display the expected patterns and magnitudes. The elasticity with respect to the outside option is considerably lower (-0.52) than the median own-price elasticity, meaning that most of the substitution occurs within gasoline products. Our median own-price elasticities are below the estimates on Houde (2012). We attribute the discrepancies to the fact that while most of our sample consists of towns and small cities, Houde (2012) estimates demand for the Quebec Metropolitan Area. Once we adjust for differences in market size, our estimates are similar. We refer the reader to Table C.9 in the appendix for a comparison to other available estimates in the literature.

To characterize the observed heterogeneity in own-price elasticities, we regress own-price elasticities on the product's brand, whether the product is premium or regular, and market size. Regular gasoline products exhibit greater elasticity than premium gasoline products: the predicted elasticity decreases by two percentage points when moving to a premium product compared to a regular product at the same location. Compared to branded products, products available at unbranded stations and stations associated with small brands exhibit a more elastic demand. Additionally, elasticities are higher in bigger markets, where more options are available. Specifically, transitioning from a market at the 10th quantile of market size to a market at the 90th is linked with an additional own-price elasticity of -1.46. We refer the reader to Table C.8 in the appendix for regression tables.

As discussed in section 3.3, YPF's market shares experienced a pronounced increase following nationalization. Our demand estimates enable us to distinguish between changes in consumption driven by price adjustments and those attributable to shifts in consumer preferences for gasoline products. The demand model suggests that part of this increase was attributed to an increase in consumers' valuation of YPF's regular gasoline. Figure 3.6 compares the observed consumption in the year after nationalization with that in the year before and presents a counterfactual scenario where consumption is modeled assuming prices remained at pre-nationalization levels. To explore whether a similar expansion in consumption would have occurred absent the nationalization, we need to understand how a *profit-maximizing* YPF would have set prices during the post-nationalization period. This analysis is presented in the subsequent section.



Note: Notes: This figure shows how changes in willingness to pay for gasoline products affected gasoline consumption after the nationalization. The white bar (*Pre*) shows observed consumption 12 months before the nationalization. The light blue bar (*Post*) shows observed consumption 12 months after the nationalization. The orange bar (*Post (No price adjustment)*) shows consumption at post-nationalization observed prices in the 12 months after the nationalization

Figure 3.6. Demand estimation: change in WTP for gasoline products

3.5.3 Supply Side: Estimation and Identification

Supply Side - Estimation

We employ a three-step procedure to estimate the supply-side primitives. In the first step, we recover marginal costs for each product before nationalization and for every non-YPF product following nationalization. In the second step, we utilize the marginal costs from all firms in the pre-nationalization phase and the marginal costs of YPF's competitors in the post-nationalization phase to estimate YPF's projected marginal costs ($\tilde{mc}_{j,t}$). Lastly, using YPF's projected marginal costs, we derive YPF's objective function and identify unobserved cost shocks for YPF in the post-nationalization period.

First step: Recover marginal costs for all products before the nationalization and for non-YPF products after the nationalization We recover marginal costs for all products before the nationalization and for all non-YPF products post-nationalization by imposing that each firm maximizes profits non-cooperatively and that firms set prices simultaneously (assumptions 1 and 2). Following this, we can invert the first-order conditions to recover marginal costs.[14]

$$mc_{j,t} = p_{j,t} - \left[\frac{\partial Q^j}{\partial p_{mj}^{ypf}}\right]^{-1} \left[Q(p_j^{ypf})\right]$$

Second step: Recover YPF's projected marginal costs We can express the marginal costs of a given product j in any market at time t as the sum of the projected marginal costs and an unobservable cost shock. Formally:

[14] For clarity, we present the equations for scenarios where each firm sells only one product in each market (i.e., no cannibalization).

$$mc_{j,t} = \underbrace{\tilde{mc}(X_t, j)}_{\text{Projected marginal cost}} + \underbrace{\varepsilon_{j,t}}_{\text{unobserved cost shock}} \tag{3.9}$$

We parametrize the projected marginal cost for product j in market $m(j)$ during period t as follows:

Assumption 4 (Additive local cost shocks)

$$\tilde{mc}_{j,t} = \underbrace{f(X_t, j)}_{\textit{marginal cost function}} + \underbrace{\nu_{m(j),t}}_{\textit{local costs shocks}} \tag{3.10}$$

In our baseline specification, we parametrize the projected marginal costs as the sum of a marginal cost function and an additive cost shock that affects all products within a specific market and time period (i.e., local cost shock), as depicted in (3.10). The marginal cost function accounts for variation in costs that arises from variables we either (i) observe (e.g., crude oil prices, distance to the refinery, brand, and product); (ii) recognize as constant across station and product (e.g., station-product specific cost differentials, such variations across different stations in labor or utility costs); or (iii) do not observe but affect all products equally over time (like fluctuations in crude oil prices or labor costs when we exclude them as explanatory variables). The local cost shock enables us to identify shifts in marginal costs common to all products within a particular market and time frame. Examples include the introduction of a new highway that diminishes transportation costs for all products in a specific market, changes in electricity prices in a particular market, or escalated municipal fees affecting markets in that municipality but not in others.

Assumption 5 (Parametrization of marginal costs function)

$$f(X_t, j) = \underbrace{\omega_{type(j),t}}_{\textit{Time and Prod-Type FE}} + \underbrace{\eta_j}_{\textit{Station-Product FE}} \tag{3.11}$$

Equation (3.11) outlines the parametrization of the marginal cost function in our baseline specification. The first term encompasses time and product type (i.e., premium and regular gasoline) fixed effects, capturing the shared components of gasoline refining across different brands. This includes factors such as crude oil prices, energy costs integral to the refining process, and the expenses associated with integrating bioethanol into the gasoline mix. The second term represents station-product fixed effects, capturing cost differences unique to specific stations and product types that remain constant over time. This encompasses variations in the marginal costs of gasoline from different refineries, disparities in local taxes and fees, labor or utility variations across stations, and differential transportation costs from the refinery to the station.

Third step: Recover YPF's Objective Function In the third step, we derive YPF's objective function based on our initial computation of YPF's marginal costs for the post-period. Specifically, we compute moment conditions by taking first-order conditions of YPF's objective function (equation (3.6)) relative to the price of each product under YPF's control:

$$Q(p_j^{ypf}) + \frac{\partial Q^j}{\partial p_{mj}^{ypf}} \times \left(p_j^{ypf} - mc_{j,t}^{ypf}\right) + \sum_{n=1}^{N} \lambda_N \times \frac{\partial CS_n}{\partial p_j^{YPF}} + \sum_{f=1}^{F} \kappa_f \times \frac{\partial \Pi_{jf}}{\partial p_j^{YPF}} = 0$$

Substituting for $mc_{j,t}$ using 3.9, imposing (3.11) and taking expectations conditioning on instruments (Z), we derive:

$$\underbrace{E\left[(p_j^{ypf} - f(X_t, j) + \nu_{m(j),t}) \mid Z\right]}_{\text{"Observed" Markup given Z}} =$$
$$\underbrace{E\left[\left(-\frac{\partial Q^j}{\partial p_{mj}^{ypf}}\right)^{-1}\left(Q(p_j^{ypf}) + \sum_{n=1}^{N}\lambda_N \times \frac{\partial CS_n}{\partial_j^{YPF}} + \sum_{f=1}^{F}\kappa_f \times \frac{\partial \Pi_{jf}}{\partial p_j^{YPF}}\right) \mid Z\right]}_{\text{Predicted Markup given Z}} + \underbrace{E\left[\varepsilon_{j,t} \mid Z\right]}_{\text{Expected idiosyncratic error given Z}} \tag{3.12}$$

The fundamental assumption that underpins our identification strategy is that, after controlling for the projected marginal costs, the unobservable component of the marginal cost is uncorrelated with the instrument vector Z. We employ two categories of instruments:

1. Demographic characteristics at the provincial level, specifically the combination of income level and province.

2. YPF's market shares in the period before nationalization, denoted by S, for each market.

Formally, our assumption is as follows:

Assumption 6 (Conditional Independence of Idiosyncratic Cost Shocks)

$$\begin{aligned} &E\left[\varepsilon_{j,t} \mid \textit{product type} = p, \textit{income} = \textit{inc}, \textit{province type} = \textit{prov}\right] = 0 \quad \forall\, \textit{inc}, p, \textit{prov} \\ &E\left[\varepsilon_{j,t} \mid \textit{product type} = p, \textit{YPF's shares in the pre-period} = s_{m(j)}\right] = 0 \quad \forall\, p, m(j) \end{aligned} \tag{3.13}$$

Each moment condition l depends on observed prices ($\mathbf{p_l}$), a vector of projected marginal costs ($\hat{\mathbf{mc}}_l$), instruments ($\mathbf{Z}_l$), and the conduct parameters λ to be estimated.

$$
\begin{aligned}
E\left[\varepsilon_{j,t} \mid Z\right] &= 0 \\
E\left[(p_j^{ypf} - \tilde{mc}_{j,t}^{ypf}) \mid Z\right] - E\left[\left(-\frac{\partial Q^j}{\partial p_{mj}^{ypf}}\right)^{-1}\left(Q(p_j^{ypf}) - \sum_{n=1}^{N} \lambda_N \times \frac{\partial CS_n}{\partial p_j^{YPF}} + \sum_{f=1}^{F} \kappa_f \times \frac{\partial \Pi_{jf}}{\partial p_j^{YPF}}\right) \mid Z\right] &= 0
\end{aligned} \tag{3.14}
$$

Define the stacked vector of all moment conditions as $\mathbf{g}(\lambda; \mathbf{p}, \hat{\mathbf{mc}}, \mathbf{Z})$. The GMM estimator is then given by:

$$
\hat{\lambda}^{GMM} = \arg\min_{\lambda \in \Lambda} \mathbf{g}(\lambda; \mathbf{p}, \hat{\mathbf{mc}}, \mathbf{Z})' W \mathbf{g}(\lambda; \mathbf{p}, \hat{\mathbf{mc}}, \mathbf{Z})
$$

where W is a weighting matrix.

Supply Side: Identification

Identification is achieved by instruments that shift the marginal welfare function but are uncorrelated with the unobservable cost shocks (Berry and Haile, 2014). In our case, the instruments are the demographic characteristics of the area in which the station is located.

We divide our discussion of the identification of supply-side parameters into two main steps. First, we discuss why our instruments are uncorrelated with unobservable cost shocks (*validity*). Second, we discuss why they shift the marginal revenue function (*relevance*).

Instrument Validity The use of pre-nationalization data, combined with a conduct assumption, allows us to understand the cost structure of YPF in the pre-period. This means understanding if costs were systematically higher in areas with specific demographics compared to other regions. Given this information, validity requires deviations from projected marginal cost to be uncorrelated with demographic characteristics. This is still possible if cost shocks affect all stations in a given market. However, we account for that by using rivals' information in the post-nationalization period (which is captured by the local cost shock term).

A potential violation of this assumption could arise, for instance, if post-nationalization, the costs associated with YPF products experienced a surge in areas with a denser population of high-income individuals and this cost increase is unparallel by YPF's rivals (otherwise, this would be accounted by local cost shocks). This can be due to changes in how YPF transports gasoline. We have argued that this is unlikely for two reasons. First, price reductions are not correlated with distance from refineries. Second, while price responses are immediate after the nationalization, any significant change in YPF's logistics would take some time to implement.

Instrument relevance The core of the identification strategy lies in contrasting the observed average markups after nationalization with what would have been the markups set by a profit-maximizing firm under identical circumstances. Differences in markups are informative about the objective function of the SOE.

From equation (3.12), re-arranging the terms yields:

$$\underbrace{E\left[\left(-\frac{\partial Q^j}{\partial p_{mj}^{ypf}}\right)^{-1}\left(\sum_{n=1}^{N}\lambda_n \times \frac{\partial CS_n}{\partial p_j^{YPF}} + \sum_{f=1}^{F}\kappa_f \times \frac{\partial \Pi_{jf}}{\partial p_j^{YPF}}\right) \mid Z\right]}_{\text{Mark-up Differences}} =$$

$$\underbrace{E\left[(p_j^{ypf} - \tilde{mc}_{j,t}^{ypf}) \mid Z\right]}_{\text{Expected Mark-ups (Actual)}} - \underbrace{E\left[\left(-\frac{\partial Q^j}{\partial p_{mj}^{ypf}}\right)^{-1}\left(Q(p_j^{ypf})\right) \mid Z\right]}_{\text{Predicted Mark - ups (Profit Max)}}$$

which is a system of linear equations, where the only unknowns are $\lambda = [\lambda_1, \lambda_2, \dots \lambda_N,$ $\kappa_1, \kappa_2, \dots, \kappa_F]$ parameters. Identification requires that $\text{rank}(g(\lambda)) = \dim(\lambda)$.[15]

[15]If the objective function is linear in parameters, we can rearrange terms and write it as $E[P - A(P) \mid$

The intuition behind our rank condition is as follows. Several models can justify markups of regular gasoline that are below what a profit-maximizing YPF would have chosen. For instance, consider two rival models. In one, the government solely focuses on the consumer surplus of middle-income consumers, while in the other, the government only internalizes the surplus of low-income consumers. If there is only one gasoline station selling one type of gasoline, and that gasoline station is accessible to both low and high-income consumers, distinguishing between these two models is impossible. However, the scenario changes if there are two separate gasoline stations - one in a low-income area and the other in a high-income area. Assuming consumers dislike traveling between areas for gasoline, we can differentiate these models by comparing the expected markups of both stations, employing two moment conditions, one for each gasoline station.

In practice, even if we have two gasoline stations, identification might be challenging if both stations have the same proportion of low-income and middle-income consumers nearby. Intuitively, the government will charge similar prices in both stations if it targets either low-income or high-income households, and we will not be able to tell apart the two rival models. The fact that YPF has an extended network of stations and variation in how consumers are distributed across space allows us to distinguish between different models.

Another critical feature of the setting that allows identification is that YPF offers two products (i.e., regular and premium gasoline) and that consumers with different income levels are willing to pay different amounts for these products. In particular, low-income consumers are unlikely to purchase premium gasoline. So, any differential price discount between regular and premium gasoline that differs from what a profit-maximizing firm would have done is informative about YPF internalization of consumer surplus of low-income consumers vs. internalization of middle and high-income consumers.

$Z] = E[h(Z,P) \times \lambda \mid Z] + E[\varepsilon \mid Z]$. Imposing conditional independence ($E[\varepsilon \mid Z] = 0$), identification requires the system of equations to have a unique solution. This condition is guaranteed if the matrix $E[h(P,X) \mid Z]^T \times E[h(P,X) \mid Z]$ is invertible, meaning that we need $\text{rank}(E[h(P,X) \mid X]^T \times E[h(P,X) \mid Z]) \geq \dim(\lambda)$.

A last potential concern is how to tell a government that cares about consumer surplus from a government that wants to induce firm exit (which, in our specification, should be captured by a negative weight on rivals' firms). The kind of variation we use to distinguish between these two is the correlation between expected markups and rival's presence. For instance, suppose we compare two markets with similar demographic distributions: in one of these markets, YPF is a monopolist; in the other, it faces competition from a rival firm. If YPF were negatively internalizing rival's profits but not subsidizing consumers, YPF should charge markups that are below what a profit-maximizing firm would have charge, only in the market in which YPF faces competition but not in the market in which YPF is a monopolist. On the contrary, if YPF were subsidizing consumers, YPF should charge markups that are below what a profit-maximizing firm would have charged in both markets and independently of the level of competition.[16]

We complete this discussion by showing how actual markups vary with different demographic groups, how this compares to simulated parametrizations of the objective function, and how this allows us to identify YPF's objective function in our setting. We refer the reader to section C.4 for an illustration of how different models generate different patterns of markups across different regions and products.

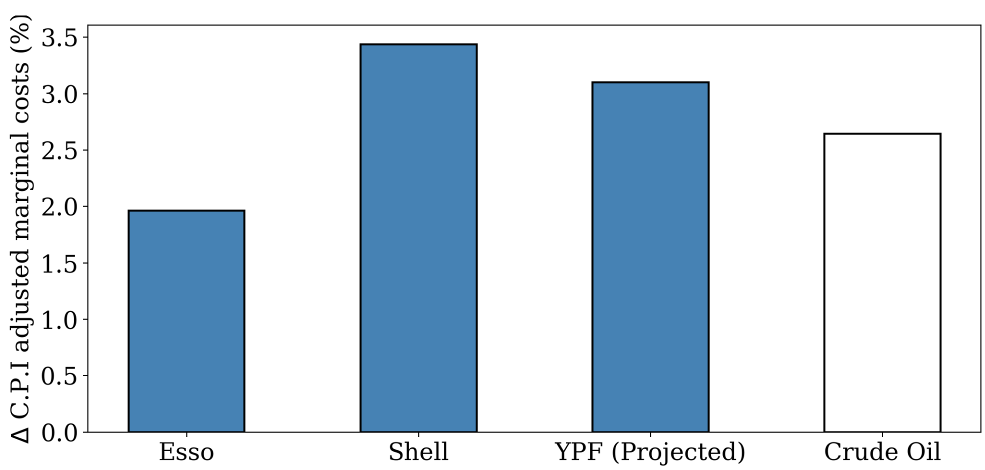
3.5.4 Supply Side: Results

Marginal Costs We regress the marginal costs of gasoline on their main gradients using only pre-nationalization estimates. Coefficients have expected signs and magnitudes. For instance, we observed a direct correlation between higher crude oil prices and increased marginal costs for gasoline. Also, premium gasoline is associated with 3% higher marginal costs than regular gasoline, consistent with high-octane premium fuel being more expensive

[16]Once we account for differences in consumer surplus gains of charging lower prices in the more concentrated market

to produce. Marginal costs are higher for stations located in remote locations. In particular, a 300km increase in distance to the refinery is associated with a marginal cost increase of 1.2 cents (1% of median marginal cost). Non-vertically integrated gasoline stations that are unbranded or affiliated with small brands- exhibit higher marginal costs. Among the first group, unbranded stations have the highest marginal costs. This is consistent with the fact that they purchase gasoline from distributors or at spot markets. Finally, we find that YPF stations have lower marginal costs than competitors, which is consistent with YPF operating at a larger scale and participating in crude oil extraction and transportation. We refer the reader to Table C.11 in the appendix for regression tables.

Using marginal cost estimates, we project YPF's marginal costs in the post-period. Figure 3.7 illustrates the results. Our projection of YPF's costs is in line with rival's costs and slightly above the evolution of crude oil prices. However, after removing the effect of local cost shocks, the median YPF station exhibited a rise in marginal cost.

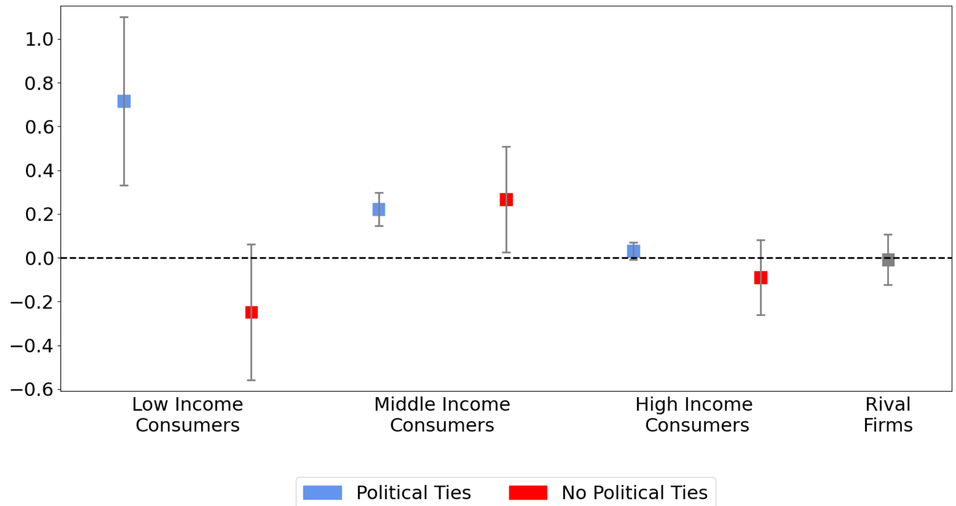


Note: Notes: This figure shows the changes in marginal costs of gasoline for different firms and crude oil prices (*Medanito*) when comparing the post-nationalization period (05-2012 to 03-2013) with the pre-nationalization period (01-2010 to 12-2012). For YPF, the figure displays estimates of projected marginal costs according to our baseline specification (see equation (3.9)). Values are expressed in CPI-adjusted pesos.

Figure 3.7. Changes in marginal costs of gasoline: by brand

YPF Objective function Figure 3.8 plots estimates and standard errors of YPF's objective function parameters, corresponding to equation 3.8. Table C.12 presents the same information in a table version. In our baseline specification, we group consumers by income levels—low, medium, and high—and by province type: shareholder and non-shareholder. We also include a parameter capturing the internalization of all firms' profits. As a result, we end up with seven different parameters to be estimated, as we normalize YPF's valuation of its profits to be equal to 1.

The results show that YPF internalizes the effects of its pricing on consumer surplus. However, not all consumers are weighted equally. YPF weighs consumer surplus differently based on income level and location. The estimates highlight significant differences in low-income categories between shareholder and non-shareholder provinces. YPF was willing to trade 1 dollar of its profits to increase the consumer surplus of low-income groups in shareholder provinces by around 0.7 dollars. Our estimates show that YPF is willing to trade off one dollar of profits to increase the consumer surplus of middle-income consumers by around 25 cents, with slightly higher estimates for those located in non-shareholder provinces. However, we cannot reject any internalization for high-income consumers. Lastly, our findings indicate that YPF doesn't account for the impact of its pricing decisions on its competitors.



Note: Note: This figure displays estimates and their 95% confidence intervals for the parameters of the goverment's objective function based on our baseline specification (refer to equation (3)). Estimates are grouped by agent type: consumers (blue and red) and firms (in grey). Additionally, they are categorized by province type: shareholders (in blue) and other provinces (in red). We refer the reader to Table C.12 in the appendix for a table version of the results.

Figure 3.8. Goverment's objective function: results

To rationalize our results, we compare the actual markups that YPF charged (based on our cost estimates) with (1) the expected markups that a profit-maximizing firm would have charged and (2) the markups that firms with different parametrizations would have charged. This exercise illustrates the discussion of subsection 3.5.3. We present this exercise in detail in section C.4 and summarize here the main results.

We defined a *subsidy* as a difference between the markups a profit-maximizing firm would have charged and those that the SOE charged. Subsidies are different in oil-producing provinces and other provinces in three dimensions. First, the magnitude of the subsidy is higher on average in oil-producing provinces, pinning down higher preferences for consumers in those provinces. Second, subsidies for premium gasoline are relatively lower in oil-producing provinces, consistent with a higher internalization of low-income households. Third, the correlation between markups and income is more pronounced in oil-producing provinces (and almost flat in the latter), consistent with a higher internalization of low and middle-income households.

Finally, we reject the possibility that lower prices are due to the government trying to induce a rival's exit. While a model that generates a rival's exit would generate lower prices in markets with higher rivals' presence, we find no correlation between subsidies and rival's presence.

Model Fit

Table 3.3 presents the results for model fit. The measure of model fit we use is based on predicting prices for each gasoline station without considering the idiosyncratic error term. The model fits the data well. Differences are below one cent for the average price of regular and premium gasoline and for the average prices at shareholders and non-shareholder provinces. The model also has a good fit of the correlation between prices and income for regular and premium gasoline at different province types and the correlation between prices and YPF's market shares in the pre-nationalization period for different products, with most differences being below 1 cent. A noticeable exception is the predicted premium gasoline prices in shareholder provinces in middle and high-income locations. In particular, the model predicts prices that are 3 to 4 cents lower.

Moment	Data	Model
E[price | regular,]	1.73	1.73
E[price | premium,]	1.93	1.93
E[price | S]	1.46	1.45
E[price | NS]	1.87	1.87
E[price | regular, low income, S]	1.63	1.63
E[price | regular, medium income, S]	1.47	1.47
E[price | regular, high income, S]	1.38	1.38
E[price | premium, low income, S]	1.84	1.84
E[price | premium, medium income, S]	1.71	1.67
E[price | premium, high income, S]	1.63	1.59
E[price | regular, low income, NS]	1.83	1.83
E[price | regular, medium income, NS]	1.82	1.82
E[price | regular, high income, NS]	1.82	1.82
E[price | premium, low income, NS]	1.99	2.00
E[price | premium, medium income, NS]	1.99	1.99
E[price | premium, high income, NS]	1.99	2.00
E[price | regular, ypf shares $<$ 33%]	1.85	1.85
E[price | regular, ypf shares $\in$ (33%;66%)]	1.77	1.76
E[price | regular, ypf shares $>$ 66%]	1.66	1.66
E[price | premium, ypf shares $<$ 33%]	1.99	1.97
E[price | premium, ypf shares $\in$ (33%;66%)]	1.95	1.94
E[price | premium, ypf shares $>$ 66%]	1.89	1.91

Note: Note: This table shows moments used for estimation and model fit.

Table 3.3. Model fit

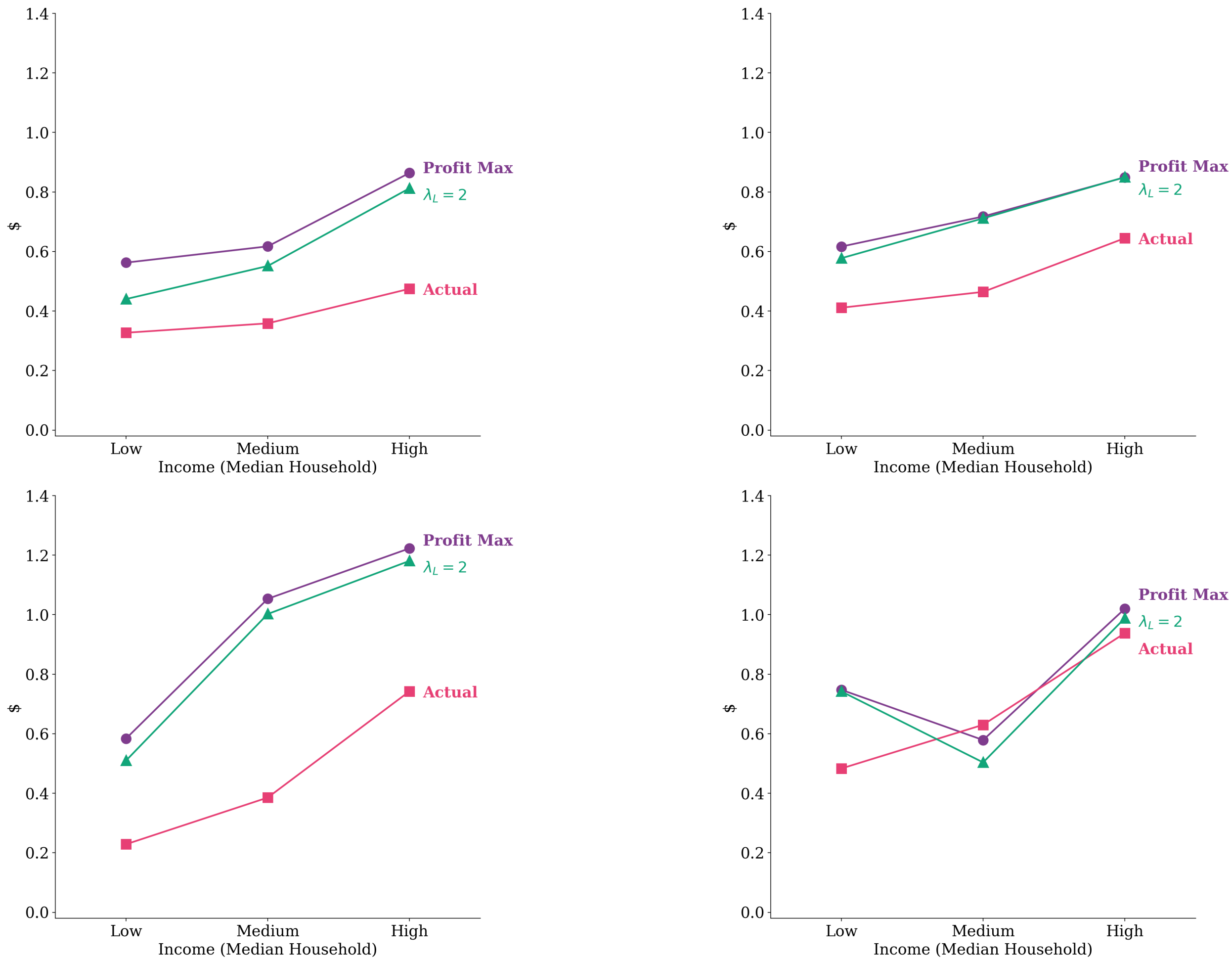
3.6 Effects of the Nationalization

In this section, we use our estimates of demand and marginal costs to evaluate the effects of the nationalization in the downstream gasoline market. Throughout this section, we compare (i) the prices we observe in the data (*actual scenario*) vs. (ii) counterfactual prices that we simulate, assuming that YPF would have been a profit-maximizing firm after the nationalization (*privatization scenario*). By comparing these two scenarios, we isolate changes in the objective function from changes in consumer preferences or costs.

Aggregate Effects The nationalization led to an expansion of the gasoline market and increased total surplus. As we previously showed, the post-nationalization period was associated with higher demand for gasoline and higher costs -due to higher crude oil prices. YPF responded by increasing prices by approximately one percent, two percentage points below the changes in crude oil prices, and six percentage points below what a profit-maximizing firm would have done in a similar scenario. Consequently, the amount of gasoline sold increased by 7% compared to the pre-nationalization period and by 4% more than what a profit-maximizing firm would have sold. See Figure C.24 (panel b) in the appendix.

Price discounts are more significant in regular (7.5%) than in premium gasoline (4.2%). This results from both YPF's direct action, which reduces prices of regular gasoline more than premium gasoline in comparison to a counterfactual scenario, and also because rival's responses were more pronounced in regular than in premium gasoline, due to the lower cross-price elasticity between YPF's and rivals' premium gasoline products. Consistent with the descriptive evidence, market expansion was led by regular gasoline, which increased by 7%.

Effect on markups Figure C.27 in the appendix presents the distribution of markups in both the observed and profit-maximizing scenarios. Interestingly, by not taking advantage of a higher willingness to pay for gasoline (especially in non-oil-producing provinces), the nationalization results in a more compressed markup distribution, particularly truncating the right tail.



Note: Note: Subfigures (a) and (b) depict markups for regular and premium gasoline as a function of the median income of households within the census block of the station's location. The purple line illustrates the profit-maximizing case, while the pink line shows the actual markups YPF set, using our cost estimates. The additional line represents the case in which the government internalizes the consumer surplus of the low-income groups (green line).

Figure 3.9. Correlation between income and mark-ups under different scenarios

Distribution and Welfare Effects As our previous estimates suggest, the state-owned enterprise exerts price discrimination differently than a profit-maximizing firm. The effects of YPF nationalization on prices vary depending on product quality and location, leading to heterogeneous consumer impacts. First, the effects on sales are more significant in shareholder provinces. Effects are more prominent not only on average but also when comparing individuals of the same income group (Table C.13). This is a direct consequence of YPF generating a price reduction on regular gasoline twice as large as the one observed in the rest of the country. Second, the group that increased consumption the most across the country is middle-income households (5%). Despite not being actively targeted, high-income groups also benefited from the policy and responded by increasing their consumption of premium (6.2%) and regular gasoline (2%). Interestingly, the effect of the policy on low-income households varies heavily depending on whether they live in an oil-producing province, and it is consistent with the SOE internalizing consumer surplus of low-income consumers exclusively in shareholder provinces.

Aggregate consumer surplus increased by 12.5% (Table 3.4). Firms are negatively affected by the nationalization. Compared to the profit-maximizing case, firms sell more gasoline at lower prices. Moreover, rivals' profits are the most affected (-12.3% vs. -2.7%). Overall, by charging lower markups on its products and forcing rivals to reduce prices, the nationalization offsets part of the distortion generated by the existence of market power and increases total surplus by 6.2%.

Benchmarking We use two counterfactual scenarios to benchmark the effects of the nationalization. The first alternative benchmark corresponds to a scenario where YPF maximizes total surplus. This means that the SOE fully internalizes consumer surplus and rival firms profits, and the consumer surplus of all consumers receives the same weight as YPF's profits (*Full CS* in Table 3.4). Intuitively, this is the best the firm can do by operating through the firms. This benchmark would have increased consumer surplus by 62% (vs. 12.5% in the actual case), reduced rivals' profits by 35%, and set YPF's profits to zero (since the SOE is doing marginal cost pricing). Additionally, we benchmark the nationalization against the case in which all firms in the industry price at marginal costs (see $p = mc$ in Table 3.4). This is the best a planner can do, absent any consideration regarding fixed costs.

	UP	UM	Full
Panel 1: Oil-Producing			
CS	-13.5%	2.0%	58.7%
Profits YPF	-3.8%	-5.8%	-100.0%
Profits rest	16.7%	4.8%	-28.6%
Total Surplus	-7.8%	0.3%	8.0%
Panel 2: Other Provinces			
CS	-1.5%	-4.5%	40.3%
Profits YPF	-4.0%	-5.8%	-100.0%
Profits rest	5.8%	13.7%	-25.9%
Total Surplus	-1.3%	-2.9%	6.0%
Panel 3: All Provinces			
CS	-4.0%	-3.1%	44.1%
Profits YPF	-3.9%	-5.8%	-100.0%
Profits rest	8.3%	11.6%	-26.5%
Total Surplus	-2.7%	-2.2%	6.4%

Note: Note: This table presents the changes in consumer surplus, profits, and total surplus by comparing four scenarios against the profit-maximizing case. The values are computed for the period from Jun-2012 to Dec-2012. The *actual* column contrasts the nationalization scenario with the profit-maximizing case. The *Full CS* column describes a scenario where YPF fully internalizes consumer surplus, treating the consumer surplus of all consumers with the same weight as YPF's profits. The $p = mc$ column corresponds to a scenario where all firms do marginal cost pricing. Lastly, the *Low Income* column represents a case where the SOE focuses exclusively on the low-income population. For the actual values, refer to Table C.15 in the appendix.

Table 3.4. Welfare effects: different scenarios vs. privatization

3.7 Implications for Policy Design

We showed that YPF affected distributional outcomes by discretionally charging different prices at different gasoline stations. Although YPF nationalization increased consumer surplus and overall welfare, it has two potentially undesirable effects from a distributional perspective. First, due to political price discrimination, the SOE charges lower markups to consumers in shareholder provinces than consumers of the same income level in non-shareholder provinces. Second, the bulk of the markup reduction ends up in the hands of middle and high-income consumers due to the lower economic price discrimination that the firm exerts.

At the time of writing this paper, a heated debate surrounds YPF. One of the two leading presidential candidates and several party members are advocating for privatization of YPF. They argue that YPF is being used for partisan political purposes and that the state is unable to manage firms efficiently. On the other hand, representatives from both major political parties in Congress are pushing to enact price regulations for YPF through legislation to address regional pricing disparities.[17]

We utilize our model to analyze the design of optimal policies. Specifically, we investigate the implications of implementing regulations that constrain the discretion of State-Owned Enterprises (SOEs) in determining prices, a practice observed in several countries where public enterprises are subject to limitations—either through legal frameworks or regulatory oversight—on their pricing and contracting decisions (see (IMF, 2020)).

These policies involve a delicate tradeoff. While they can effectively align government and societal interests by curbing the influence of lobbying and political pressures, they may also challenge the state-owned firm's core mission by limiting its flexibility to respond to market conditions.

[17] See Senator Mera Figueroa's project. See also Senator Naidenof's project

To evaluate the effects of the proposed policies, we solve YPF's pricing problem considering YPF's preferences - denoted by our estimates of its objective function - yet restricting YPF's choice set by the price rule. We study the effects of two regulatory approaches. The first regulatory approach, *uniform pricing*, involves setting equal prices for identical products at every gasoline station. The second regulatory approach, referred to as *uniform markup*, requires YPF to apply identical unit markups for each product type nationwide. We compare these policies to the current status quo of nationalization under discretion and the proposed privatization.

We model this situation as a constrained optimization problem for the SOE. The SOE chooses prices based on their preferences but is constrained by the set of prices (or markups) it can choose. Given a price rule $\bar{f}(p)$ imposed by the congress, the SOE solves:

$$\begin{aligned} \underset{\boldsymbol{p}_{YPF}}{\text{maximize}} \quad & W(\hat{\lambda}, \hat{\kappa}, \boldsymbol{p}_{YPF}) \\ \text{subject to} \quad & f(\boldsymbol{p}_{YPF}) = \bar{f}(\boldsymbol{p}_{YPF}) \end{aligned}$$

where $W(\hat{\lambda}, \hat{\kappa}, \boldsymbol{p}_{YPF})$ is the objective function we estimate in section 3.5.

Our analysis reveals that none of these policies dominates the others in all dimensions. Trade-offs exist concerning taxpayer costs, efficacy in curbing political price discrimination, impact on total consumer surplus, and overall welfare implications.

Privatization From taxpayers' perspective, privatization is the best policy since, by construction, it maximizes YPF profits. It is also preferred by rival firms and, by construction, reverts all distributional outcomes generated by nationalization. However, it is the worst policy for consumers and overall welfare (See Table 3.4 column a).

Uniform Pricing Nationalization under uniform pricing is the most effective policy to reduce the gap between consumers in oil-producing and non-oil-producing provinces and also for low-income households in non-oil-producing provinces. However, it is associated with higher social costs: it offsets half of the welfare gains generated by the nationalization and increases the burden on taxpayers by 4%.

Two forces explained the overall welfare loss associated with the uniform pricing rule. First, the uniform pricing rule generates a worse alignment between prices and marginal costs than the nationalization under the discretion scenario (Figure C.28 in the appendix). Second, the uniform pricing rule softens competition, reducing the relevance of equilibrium effects. In particular, rivals become less responsive to YPF's actions under the uniform pricing rule, leading to higher average prices and lower overall welfare. This finding is consistent with previous results in the literature on imperfect competition under uniform pricing (Adams and Williams, 2019). Figure C.30 in the appendix compares YPF and rival's responses under discretion and a uniform pricing rule.

Uniform Markups We find that a uniform markup rule improves allocative efficiency in comparison to uniform pricing—because of a closer alignment between prices and costs– but not in comparison to nationalization under discretion—since the government responds to the mandate by choosing higher markups on average. Interestingly, the uniform markup rule is less effective than uniform pricing in preventing the government from favoring targeted households. There are two different reasons why the Uniform markup policy generates these distributional outcomes. First, it is due to the negative correlation between marginal costs and SOE's preferences for specific consumer groups. Since cities with a higher proportion of middle-income consumers are located relatively near the refineries, they access products with lower marginal costs, and therefore, the uniform markup policy makes them even better off. A similar effect is observed for consumers in oil-producing provinces due to having lower taxes. Moreover, doing *economic price discrimination*, which is charging higher markups to consumers with higher willingness to pay, is progressive in our context. In other words, a uniform markup rule is close to what a planner that only cares about higher-income households would have chosen (See section C.4).

	UP	UM	Full
Panel 1: Oil-Producing			
CS	-13.5%	2.0%	58.7%
Profits YPF	-3.8%	-5.8%	-100.0%
Profits rest	16.7%	4.8%	-28.6%
Total Surplus	-7.8%	0.3%	8.0%
Panel 2: Other Provinces			
CS	-1.5%	-4.5%	40.3%
Profits YPF	-4.0%	-5.8%	-100.0%
Profits rest	5.8%	13.7%	-25.9%
Total Surplus	-1.3%	-2.9%	6.0%
Panel 3: All Provinces			
CS	-4.0%	-3.1%	44.1%
Profits YPF	-3.9%	-5.8%	-100.0%
Profits rest	8.3%	11.6%	-26.5%
Total Surplus	-2.7%	-2.2%	6.4%

Note: Note: This table displays changes in consumer surplus, profits, and total surplus by comparing three different scenarios against the actual case (nationalization under discretion) from June 2012 to December 2012. The *Uniform Pricing* column shows the effects of the uniform pricing policy in contrast to the actual scenario (nationalization under discretion); *Uniform Markups* column shows the effects of applying the uniform markups policy; *Full CS* column outlines the effects of a scenario where YPF fully internalizes consumer surplus, treating the consumer surplus of all consumers equivalently to YPF's profits. Refer to Table C.16 in the appendix for detailed values.

Table 3.5. Effects of price rules on welfare: pricing rules vs discretion

	UP	UM	Full
Panel 1: Oil-Producing			
CS	-13.5%	2.0%	58.7%
High Income	-14.3%	2.6%	40.7%
Middle Income	-28.6%	-14.3%	307.1%
Low Income	42.9%	14.3%	157.1%
Panel 2: Other Provinces			
CS	-1.5%	-4.5%	40.3%
High Income	-2.2%	-2.6%	18.1%
Middle Income	-3.0%	-20.8%	199.0%
Low Income	29.2%	-4.2%	170.8%
Panel 3: All Provinces			
CS	-4.0%	-3.1%	44.1%
High Income	-4.8%	-1.6%	22.9%
Middle Income	-6.1%	-20.0%	212.2%
Low Income	32.3%	3.2%	171.0%

Note: Note: This table presents changes in consumer surplus by income group and province type when comparing three different scenarios against the actual case (nationalization under discretion) for the period Jun-2012 to Dec-2012. The *Uniform Pricing* represents the effects of applying the uniform pricing policy; *Uniform Markups* represents the effects of applying the uniform markups policy; *Full CS* describes a scenario where YPF fully internalizes consumer surplus, equating the consumer surplus of all consumers to YPF's profits. For detailed values, refer to Table C.17 in the appendix.

Table 3.6. Effects of price rules on consumer surplus: pricing rules vs discretion

3.8 Conclusion

We study the nationalization of Argentina's leading oil and gas company and assess its effects on the retail gasoline market. We showed how to use microdata and modern empirical tools to isolate the effect of the nationalization from confounding factors such as changes in demand and costs and recover the firm's objective function.

Our analysis uncovers a fundamental trade-off inherent in public provision. On the one hand, the SOE's actions benefit consumers on average and enhance allocative efficiency by charging lower markups. Moreover, the state-owned firm engages in less economic price discrimination. These two actions lead to a closer alignment between prices and costs. On the other hand, the firm imposes varied prices based on consumers' political ties, leading to undesirable distributional outcomes.

We also explore the effects of different policy tools that aim to align government and social preferences. Our analysis reveals that none of these policies dominates the others in all dimensions. Trade-offs exist concerning taxpayer costs, efficacy in curbing political price discrimination, impact on total consumer surplus, and overall welfare implications. Who are the groups with the most influence on the firm, how much (or less) costly the products they consume are in comparison to the rest of the population, how many instruments does the government have to discriminate among consumers, and how does the congress trade-off taxpayer costs, efficiency, and equity are essential factors in determining the optimal policy.

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Appendix A

Appendix to Chapter One

A.1 Appendix: Market Description

A.1.1 Data Summary Statistics

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

	All	Final Sample
Individuals	2208	1305
Observations	4978	2850

Table A.1.1. Data Summary Statistics

A.1.2 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.

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.

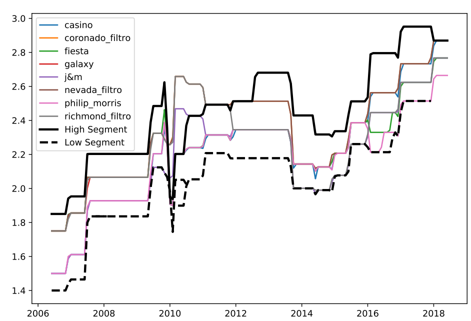
Within each of these categories, there are two types of vertical "qualities": standard and premium. The low-cost segment, which is common in other countries, did not develop in Uruguay. Table A.1.2 shows market shares across these dimensions and firms. The premium segment is small, and only BAT and Philip Morris sell premium cigarettes. However, these segments are not completely isolated markets. There exists non-trivial substitution between premium-light categories.

	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	-	-	-

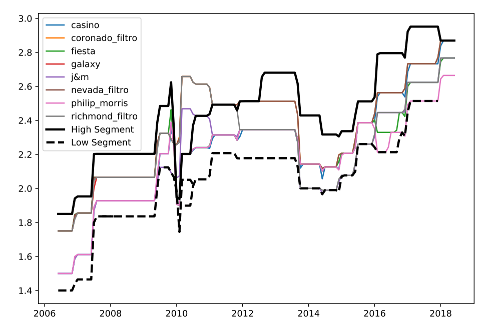
Table A.1.2. Market Share by Segment and Firm.

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 A.1.1a 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.



(a) High Segment Prices.



(b) 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.

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 A.1.2). 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.

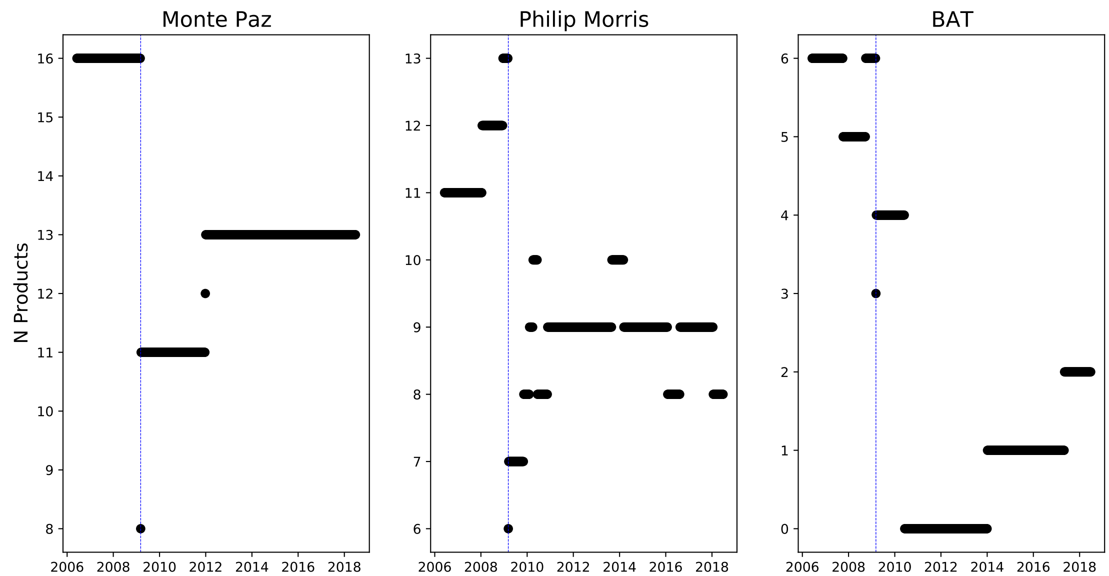


Figure A.1.2. Evolution of firms' product portfolio.

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 A.1.3 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

Table A.1.3. Summary Statistics by Segment

A.1.3 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.

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

	(1)	(2)
	OLS	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

Table A.1.4. Structural State Dependence versus Spurious Dependence

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.[1] Table A.1.4 shows the results, indicating that state dependence is a relevant force in our setting.

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

A.1.4 Other Tables

	EM1	EM2	EM3	EM4	EM5	IM1	IM2	IM3	IM4	IM5
Previous Smoker	0.641	0.638	0.599	-	0.303	3.907	3.586	-7.018	-	-38.296
	(0.024)	(0.024)	(0.027)	-	(0.061)	(1.358)	(1.324)	(1.018)	-	(1.729)
Quantity Smoked	-	-	0.004	0.003	-	-	-	0.670	0.619	-
	-	-	(0.001)	(0.001)	-	-	-	(0.017)	(0.017)	-
log(Addiction Stock)	-	-	-	-	0.061	-	-	-	-	7.291
	-	-	-	-	(0.009)	-	-	-	-	(0.233)
R^2	0.252	0.256	0.306	0.315	0.312	0.004	0.058	0.486	0.486	0.377
N	2770.0	2770.0	2544.0	2544.0	2544.0	1944.0	1944.0	1873.0	1873.0	1873.0
Product FE	No	No	No	Yes	No	No	No	No	Yes	No
Demos FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes

Note:

Table A.1.5. Extensive and Intensive Margin of Consumption

A.1.5 Other Figures

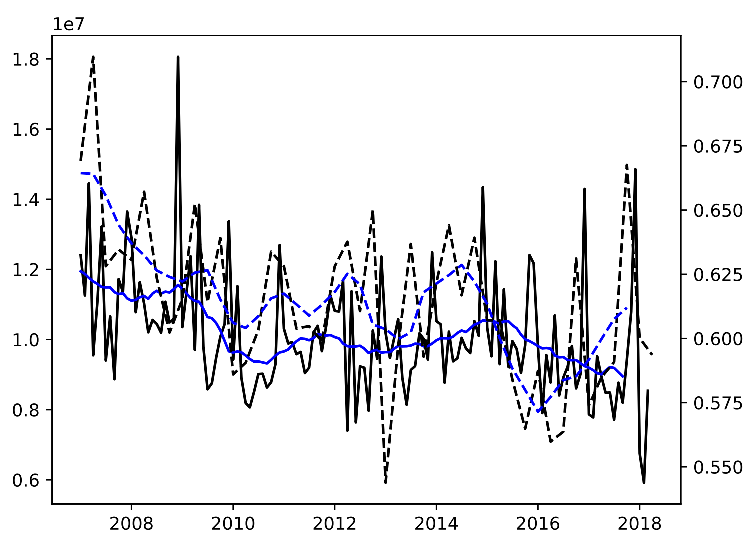


Figure A.1.3. Aggregate National Sales and Sample Aggregate Sales

Figure A.1.4. Plain Packages

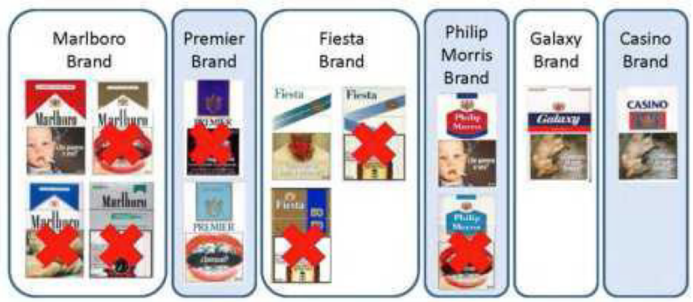


Figure A.1.5. Philip Morris' portfolio and products affected by OPPB

A.2 Appendix: Additional Modeling Details

A.2.1 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 $\gimel_f$ 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

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

The indicator function $1 \left\{ \gimel_f = \text{argmax}_J \left(\beta \int_{\gimel_{-f}} V(J, \gimel_{-f}) dF(\gimel_{-f} | \sigma^{\phi}_{-f}) - \sum_{k:J_k=1} \Theta_k \right) \right\}$ defines an area of integration $A^{\gimel_f}$. This area is the region of realizations of $\Theta_f \in \mathbb{R}^K$ over which offering $\gimel_f$ 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 $A_{k(f)} = \{\Theta_f \in \cup_{\{\gimel_f : \gimel_{fk}=1\}} A_k^{\mathbb{J}_f}\}$. 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

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

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 the company's operations, considering the profits of the whole firm. Hence, we still account for possible cannibalization effects.

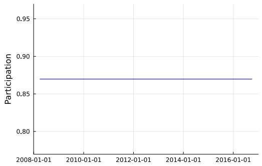
A.3 Robustness Checks and Additional Results

A.3.1 Model Fit and Robustness

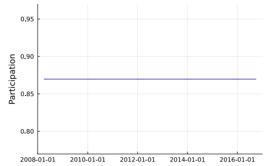
	Outside	MP Flag.	MP Light	MP Other	PM Flag.	PM Prem	PM Light	PM Light Prem	PM Other	BAT	BAT Prem
Outside	0.78, 0.78	0.17, 0.09	0.01, 0.03	0.0, 0.01	0.01, 0.04	0.02, 0.03	0.01, 0.01	0.01, 0.01	nan, nan	nan, nan	0.0, 0.01
MP Flag	0.18, 0.13	0.74, 0.79	0.04, 0.02	0.0, 0.01	0.01, 0.02	0.02, 0.02	0.0, 0.01	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.

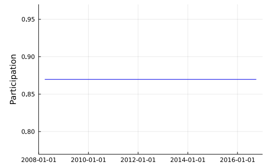
Table A.3.1. Predicted and Observed Switching



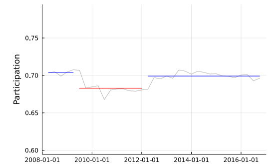
(a) Monte Paz, Flagship



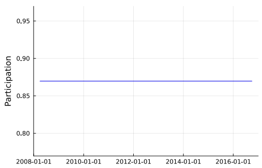
(b) Monte Paz, Other Regular



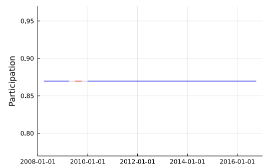
(c) Monte Paz, Light



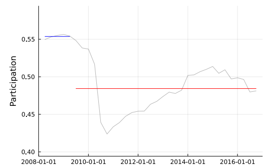
(d) Monte Paz, Specials



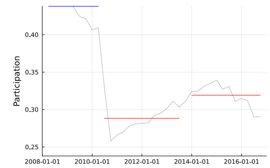
(e) Philip Morris, Flagship



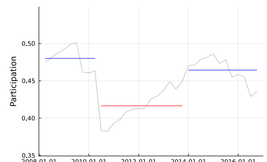
(f) Philip Morris, Light



(g) Philip Morris, Other Regular

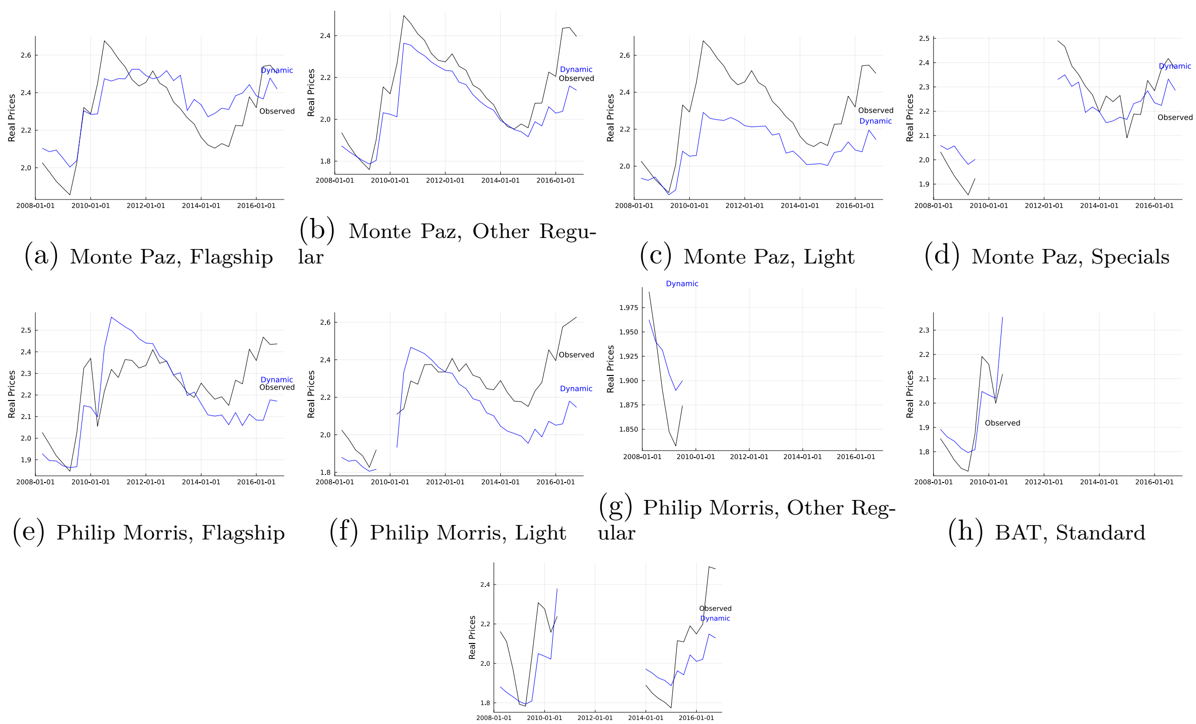


(h) BAT, Standard



(i) BAT, Premium

Figure A.3.1. Compare Observed 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

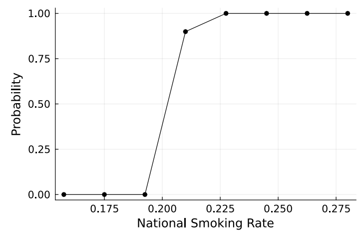
(h) BAT, Standard

(i) BAT, Premium

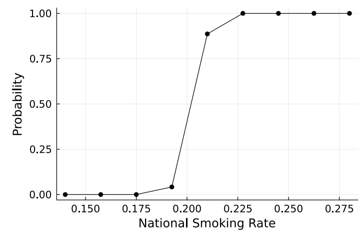
Figure A.3.2. Compare Observed and Simulated Prices.

A.3.2 Additional Results

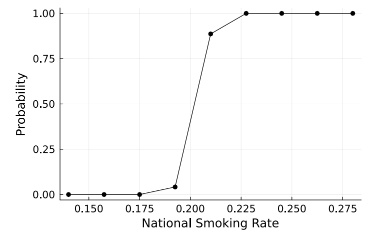
Stationary Distribution of Consumption and Product Portfolios



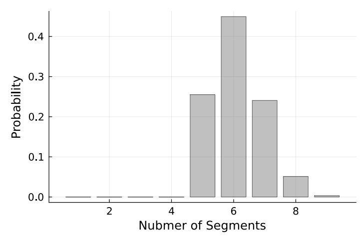
(a) Distribution of Aggregate Consumption - Baseline



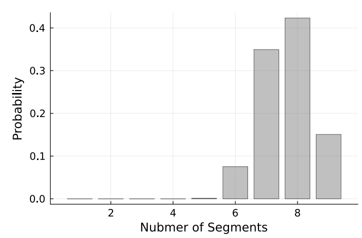
(b) Distribution of Aggregate Consumption - No Addiction



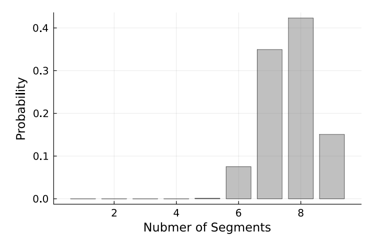
(c) Distribution of Aggregate Consumption - No Loyalty



(d) Distribution of Products - Baseline



(e) Distribution of Products - No Addiction

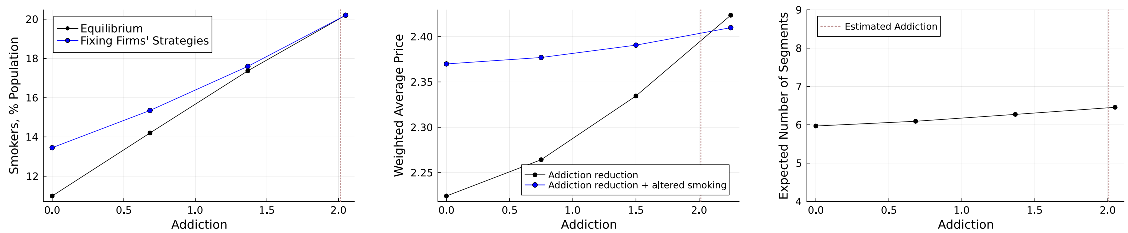


(f) Distribution of Products - No Loyalty

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 A.3.3. Stationary Distribution of Consumption and Product Portfolios

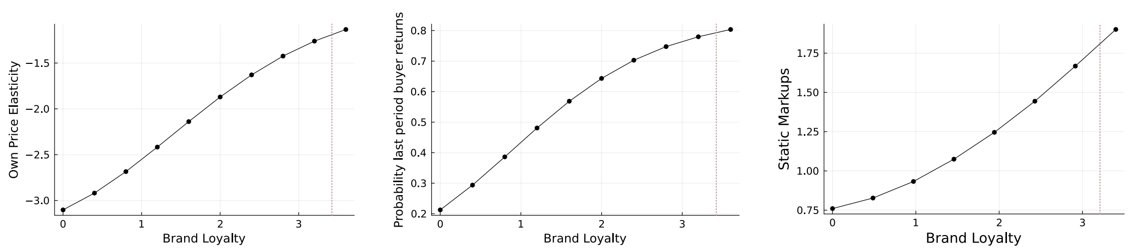
Addiction



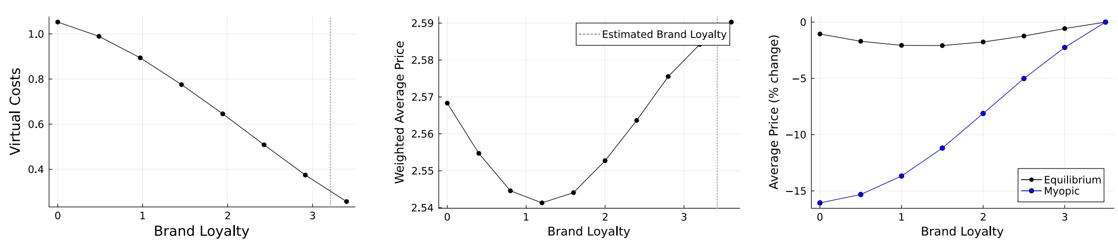
Note: For each level of inertia, we solve for equilibrium policies for prices and market participation. Then, we simulate the industry evolution over 50 periods, replicated 2,500 times from a null industry scenario. The depicted results are the averages across time and simulations. For the results where we fix firms' strategies, we solve the equilibrium at the baseline level of inertia and then simulate the economy modifying consumer preferences. The 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.

Figure A.3.4. Equilibrium Outcomes under Alternative Levels of Addiction

Brand Loyalty



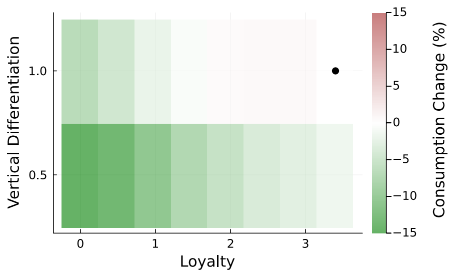
(a) Elasticity (b) Probability of Returning (c) Static Markups



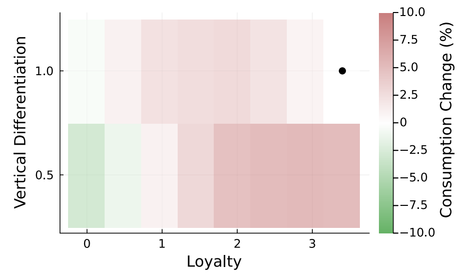
(d) Virtual Costs (e) Weighted average price (f) Weighted average “myopic” price

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.

Figure A.3.5. Summary Statistics for Intermediate Levels of Brand Loyalty



(a) Fixed Participation Policies



(b) Full Equilibrium

Figure A.3.6. Vertical Differentiation

A.4 Appendix: Computational Implementation

A.4.1 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.

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 $e \in \mathcal{E}$ 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

$$V_f(x, \gimel, e; q) = \sum_{n=0}^{N} q_n^{f,\gimel,e} T_n(x) \tag{A.1}$$

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 $\{q_n^{f,\gimel,e}\}_{n\in\{1,..,N\},\gimel\in\mathcal{J}}$, 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 $\{z_i^f(\gimel, e) \in \mathcal{S}^{f,\gimel,e}\}$ for each firm f, choice set $\gimel$ and exogenous state e, where to solve the value function –and corresponding policies.[2] Choosing the nodes $\mathcal{S}^{f,\gimel,e}$ 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.[3] 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 $\epsilon_i^{f,\gimel,e} = V_f(z_i^f(\gimel, e), \gimel, e) - V_f(z_i^f(\gimel, e), \gimel, e; q)$, that is

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

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

[3]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.

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.

Updating Firms Beliefs

We enter each step k of the iteration holding $\hat{q}_{k-1}^{f,\daleth,e}$, $\sigma_{k-1}^{p}, \sigma_{k-1}^{\phi}$ in memory. Here, $\sigma^{p}, \sigma^{\phi}$ refers also to prices and probabilities of participation for each product j at each node $z_i^f(\daleth, e)$ for each choice set $\daleth$ and exogenous state e, evaluated by each firm f.[4]

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.4.2 describes how firms form beliefs about payoff relevant states from information sets I_f, i.e from $(z_i^f, \daleth, e)$. 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.[5] 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 $(z_i^{-f}, \daleth, e)$. 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 $z_i^f(\daleth, e)$. 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

$$S_{jt}^f(z_i^f(\daleth, e), \daleth, e; \sigma) = \sum_{s=1}^{F} \sum_{n=1}^{N} S_{snjt}(p_{ft}, \mathbb{J}, e; \sigma_{-f}(I_{-f}^f); \mu^D) \times S_{s,t-1}^f \times w[n|k] \tag{A.2}$$

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

[5]The suprascripts reflect the agent forming beliefs.

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 $S_t^f(z_i^f(\beth, e), \beth, e; \sigma_k^p)$, following Equation A.2. Then, participation best responses are determined by evaluating the right-hand side of the participation fixed-point problem, using $V_f(x, \beth, e; \hat{q}_k)$ evaluated at $x = S_{jt}^f(z_i^f(\beth, e), \beth, e; \sigma_k^p)$. 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.

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 $z_i^f(\beth, e)$ for each choice set and exogenous states, holding rivals' strategies fixed: $S_t^f(z_i^f(\beth, e), \beth, e; \sigma_{k-1,-f}^p, p_j)$.

$S_t^f(z_i^f(\beth, e), \beth, e; \sigma_{k-1,-f}^p, p_j)$ 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, $V_f(x, \beth, e; \hat{q}_{k-1})$ and evaluate it at $S_t^f(z_i^f(\beth, e), \beth, e; \sigma_{k-1,-f}^p, p_j)$. 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.4.5.

Hence, evaluating the right-hand side of Equation 2.13 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.

Value function update

Finally, we update the values at each interpolating node z_i, choice set $\gimel$ and exogenous state e, $V_{k+1}(z_i, \gimel, e)$, using $\sigma^p_{kf}(z^f_i, \gimel, e)$, $\sigma^\phi_{kf}(S^f, \gimel, e')$, and $V_{fk}(S^f, \gimel', e', \hat{q}_k)$. 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[6]

$$\begin{aligned}
&V_{f,k+1}(z^f_i, \gimel, e) = M \times S^f_{jt}(z^f_i, \gimel, e; \sigma^p_k) \times (\sigma^p_{kj(f)}(z^f_i, \gimel, e) - c_{j(f)}(e)) - \\
&\sum_{e' \in \mathcal{E}} \Big(\phi_{kj(f)}(S^f_t(z^f_i, \gimel, e; \sigma^p_k), \gimel, e') \times \theta_{FC} - \Big[1 - \phi_{kj(f)}(S^f_t(z^f_i, \gimel, e; \sigma^p_k), \gimel, e')\Big] \times \bar{\Theta}(S^f_t(z^f_i, \gimel, e; \sigma^p_k), \gimel, e'; \phi_k) Pr(e'|e)\Big) + \\
&\sum_{e' \in \mathcal{E}} \sum_{\gimel' \in \mathcal{J}} V_{f,k}(S^f_t(z^f_i, \gimel, e; \sigma^p_k), \gimel', e'; \hat{q}_k) Pr(\gimel'|\phi_k) Pr(e'|e))
\end{aligned} \tag{A.3}$$

Then, we proceed to the next iteration. Let Ψ^p and Ψ^ϕ refer to the RHS of Equation 2.13 and Equation 1.5 respectively, and denote Equation A.3 the Bellman Equation. Algorithm 1 describes the algorithm used to solve for the equilibrium.

[6]We are omitting the explicit dependence of z^f_i on $\gimel$ and e to avoid loading the notation.

Algorithm 1 Equilibrium Solver

Choose projection nodes $\mathcal{S} \rightarrow$ state space is $\mathcal{X} = \mathcal{S} \times \mathcal{J}$.

Set $V_f^0[x] \quad \forall x \in \mathcal{X}, f$

---

while $crit^V > tol^V$ **do**

  while $crit^\phi > tol^\phi$ or $\text{iter}^\phi < \text{maxiter}(k_\phi)$ **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 $\text{iter}^p < \text{maxiter}(k_p)$ **do**

    $\nabla_S V_f(S^f_{k_p-1}(\sigma^p_{k_p-1}); \hat{q}_{k-1}) \leftarrow$ derivative of Chebyshev polynomials

    $\nabla_S \sigma^\phi_k at S^f_{k_p-1}(\sigma^p_{k_p-1}) \leftarrow$ by IFT

    $\sigma^p_{k_p} \leftarrow \Psi^p \left(S^f_{k_p-1}, \nabla_S V_f, \nabla_S \sigma^\phi_k, Pr(\beth'|\beth), Pr(e'|e) \right)$

    $S^f_{k_p} \leftarrow \sigma^p_{k_p}$ according to Equation A.2

    $crit^p = ||\sigma^p_{k+1(k_V)} - \sigma^p_{k(k_V)}|| / ||\sigma^p_{k(k_V)}||$

  end while

  Update $V_f^k \leftarrow$ according to Equation A.3

  Compute $\{\hat{q}_k\}$ by OLS.

  $crit^V = ||V_k - V_{k-1}|| / ||V_{k-1}||$

end while

A.4.2 Beliefs Computation

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

$$S_{k,t-1}^{e(f)}(\omega_f, I_f) = \begin{cases} S_{k,t-1}^{f} & k \in T^f \\ \\ \omega_k|I_f & \text{otherwise} \end{cases} \tag{A.4}$$

where the ω_f argument reflects that $S_{k,t-1}^{e(f)}(., I_f)$ 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, $(S_{t-1}^f, \bar{S}_{t-1}^f)$ 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 $S_{k,t-1}^{e(f)}$. 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 $p_t = (\sigma_f^p(I_f), \sigma_{-f}^p(\zeta_f))$, 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

$$\pi^{e(f)}(I_f; \sigma) = M \times \int \left\{ S^{e(f)}(\omega_f, \zeta_f, I_f; \sigma) \times (\sigma^p_f - c_f) - E_\Theta \left[\Theta_f \times 1\{\Theta_f \leq \bar{\Theta}(I_f, \sigma^\phi_{-f}(\zeta_f))\} \right] \right\} pr(\zeta_f|I_f) pr(\omega_f|I_f) \quad \text{(A.5)}$$

A.4.3 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.

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 $S^{ss}(\beth) = S(S^{ss}, \beth, P)$. 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

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**

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 $\beth$, assuming it will remain constant in the future.

A.4.4 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

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

A.4.5 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

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

Now, assuming fixed costs are exponentially distributed, we have

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

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

$$\nabla\phi_s = -(\nabla F_{\phi}^{\phi})^{-1}\nabla F_s^{\phi} \tag{A.6}$$

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,

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

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

A.4.6 Equilibrium Behavior - Goodness of Fit

Beliefs Consistency

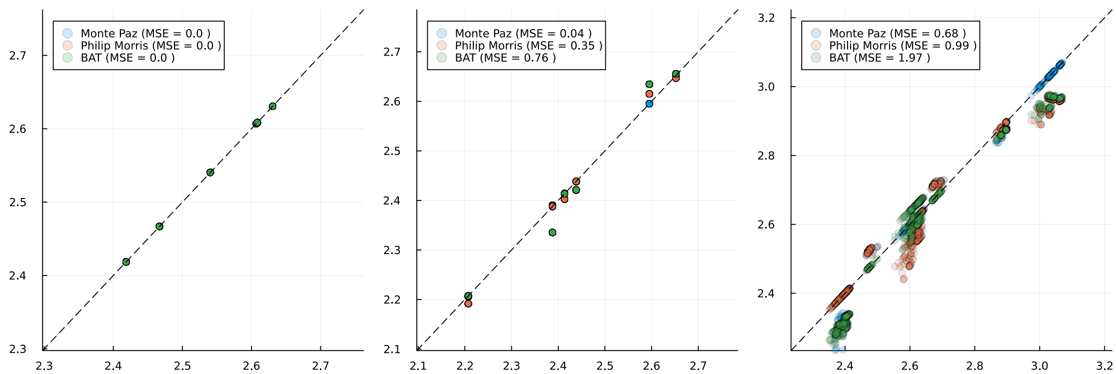


Figure A.4.1. MSE Expectation versus Observed Outcomes - Market Shares

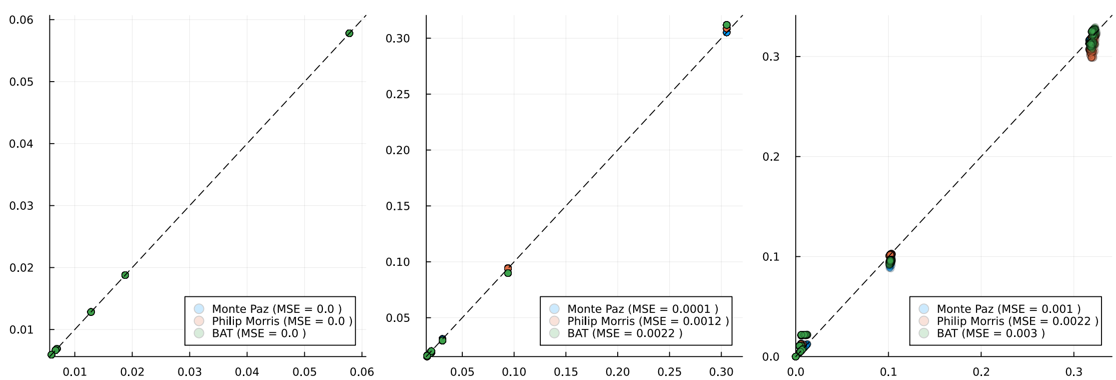
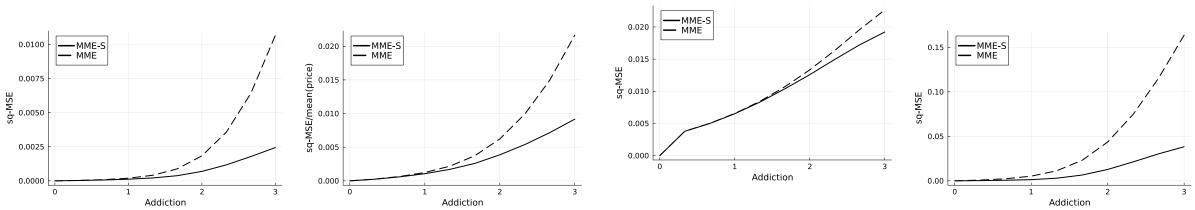


Figure A.4.2. MSE Expectation versus Observed Outcomes - Prices

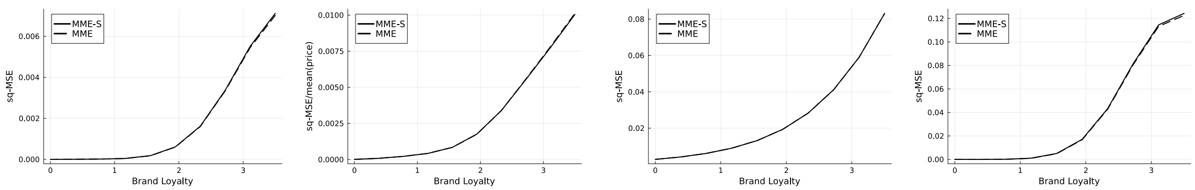
	No Dynamics		No Entry		Baseline	
	Price MSE	Share MSE	Price MSE	Share MSE	Price MSE	Share MSE
Monte Paz	6.30e-09	2.72e-11	3.53e-02	1.07e-04	6.83e-01	9.52e-04
Philip Morris	5.31e-09	4.13e-11	3.54e-01	1.17e-03	9.94e-01	2.18e-03
British American Tobacco	1.86e-08	9.71e-11	7.57e-01	2.20e-03	1.97e+00	2.97e-03

Table A.4.1. MSE comparison across models

Long-Run Outcomes under Alternative Equilibrium Definitions



(a) Market Shares - Addiction (b) Prices - Addiction (c) Switching Prob. - Addiction (d) Elasticity - Addiction



(e) Market Shares - Loyalty (f) Prices - Loyalty (g) Switching Prob. - Loyalty (h) Elasticity - Loyalty

Figure A.4.3. MSE of equilibrium outcomes over the stationary distribution - Addiction vs. Loyalty

A.4.7 Supply Estimation

Moment Selection and Empirical Objective Function

Let $q_1(\chi_{kt}, \mathbb{X}_{kt}, \theta) = \chi_{kt} - E[\sigma_k^{\chi}(\tilde{S}_{t-1}^{f}, \mathbb{J}_t, \delta_t, tax_t; \epsilon_t, \Theta_{kt}; \theta_0)|\mathbb{X}_{kt}]$, $q_2(p_{kt}, \mathbb{X}_{kt}, \theta) = p_{kt} -$ $E[\sigma^p(\tilde{S}_{t-1}, \mathbb{J}_t, \delta_t, tax_t; \epsilon_t; \theta)|\mathbb{X}_{kt}]$, 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,

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

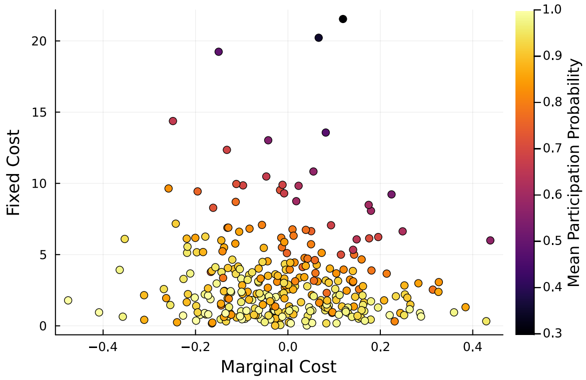
where W is a positive definite weighting matrix.

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

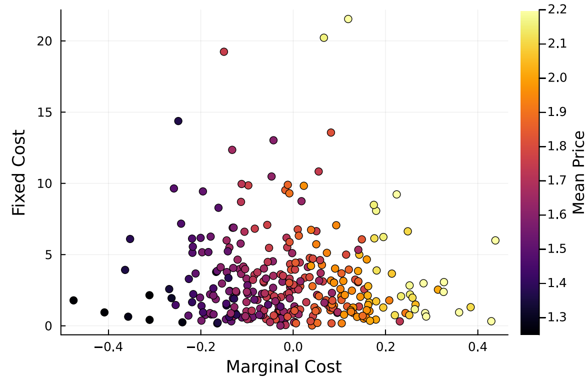
$$\hat{\theta} = \arg\min_{\theta} G_n(\theta)$$

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

Identification — Plane cuts implied by data. In Section 2.4 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 A.4.4 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



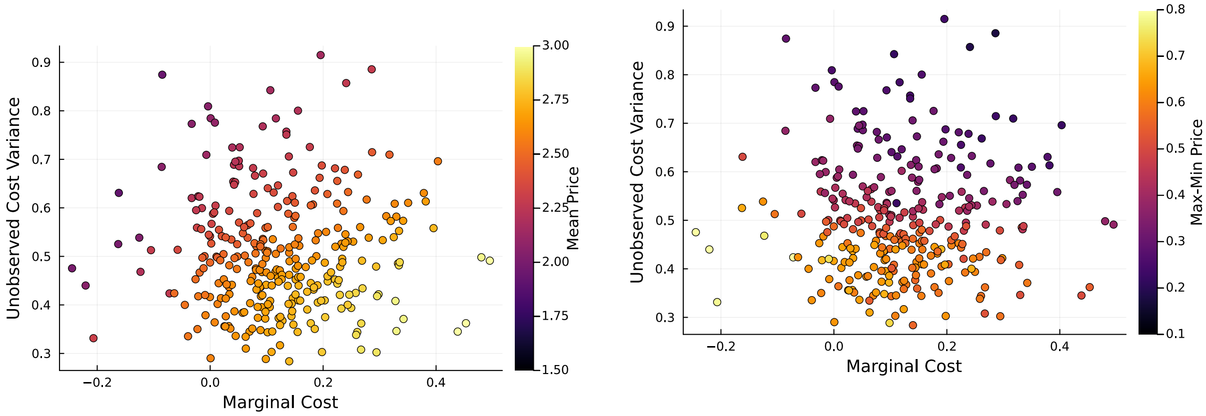
(a) Participation Rates



(b) Average Prices

Figure A.4.4. Identification of Fixed and Marginal costs, an illustration with BAT prices and participation rates.

We then observe that cost pass-through together with conduct also help ups identify the unobserved cost shocks. Figure A.4.5 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.



(a) Average Prices

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

Figure A.4.5. Identification of Unobserved Variance, an illustration with Monte Paz prices

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

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

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

$$\theta_k^{vc} = \mu_k^{vc} + \sigma^{vc}\epsilon_k^{vc}$$
$$\theta_S = e^{\mu^S + \sigma^S \epsilon^S}$$
$$\theta_R = e^{\mu^R + \sigma^R \epsilon^R}$$
$$\sigma_\epsilon = e^{\mu^{\sigma_\epsilon} + \sigma^{\sigma_\epsilon}\epsilon^{\sigma_\epsilon}}$$

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

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

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

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

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

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

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

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

$$\hat{\mu}, \hat{\sigma} = \arg\min \tilde{G}_n(\mu,\sigma) = \frac{1}{T \times N \times S} \sum_{t,k,s} \left(g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; u_s) \frac{f(u_s|\mu,\sigma)}{g(u_s)} \right)' W \left(g(\mathbb{X}_{kt}, p_{kt}, \chi_{kt}; u_s) \frac{f(u_s|\mu,\sigma)}{g(u_s)} \right) \tag{A.7}$$

The critical aspect of Equation A.7 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.

A.5 Appendix: Convergence and Multiplicity

A.5.1 Convergence & Existence

As we commented in Section 1.3, 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 A.6. 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.

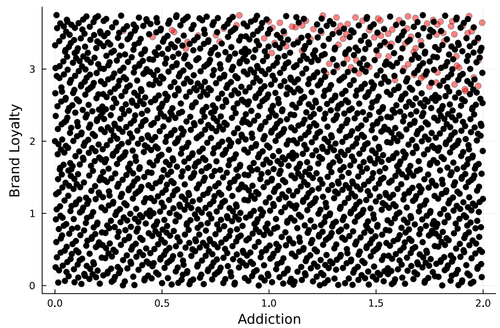


Figure A.6. Convergence Plots

A.5.2 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 A.2 shows the results of the regressions on shares, and Table A.3 on prices.

	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 A.2. Regression of equilibrium shares 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:

Table A.3. Regression of equilibrium prices of the game without entry and exit, on primitives

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.[7] The equilibrium bounds are narrow for large regions of the parameter space, indicating that the equilibrium is likely to be unique. Moreover, we employ homotopy to find all equilibria of the game as in Besanko

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

et al. (2010). Again, we find no evidence of multiplicity.[8]

A.5.3 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 A.4, Table A.5, and Table A.6 show the results of the regressions. We find that the primitives almost perfectly explain the equilibrium outcomes after we follow such equilibrium selection.

[8] pending

	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

Table A.4. Regression of Equilibrium Participation on Primitives

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%). 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.

	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 A.5. Regression of Equilibrium Prices 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

Table A.6. Regression of Equilibrium Shares on Primitives

Appendix B

Appendix to Chapter Two

B.1 Data and Summary Statistics

	EM1	EM2	EM3	EM4	EM5	IM1	IM2	IM3	IM4	IM
Previous Smoker	0.641	0.638	0.599	-	0.303	3.907	3.586	-7.018	-	-38
	(0.024)	(0.024)	(0.027)	-	(0.061)	(1.358)	(1.324)	(1.018)	-	(1.7
Quantity Smoked	-	-	0.004	0.003	-	-	-	0.670	0.619	-
	-	-	(0.001)	(0.001)	-	-	-	(0.017)	(0.017)	-
log(Addiction Stock)	-	-	-	-	0.061	-	-	-	-	7.2
	-	-	-	-	(0.009)	-	-	-	-	(0.2
R^2	0.252	0.256	0.306	0.315	0.312	0.004	0.058	0.486	0.486	0.3
N	2770.0	2770.0	2544.0	2544.0	2544.0	1944.0	1944.0	1873.0	1873.0	187
Product FE	No	No	No	Yes	No	No	No	No	Yes	N
Demos FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Y

Note:

Table B.1.1. Extensive and Intensive Margin of Consumption

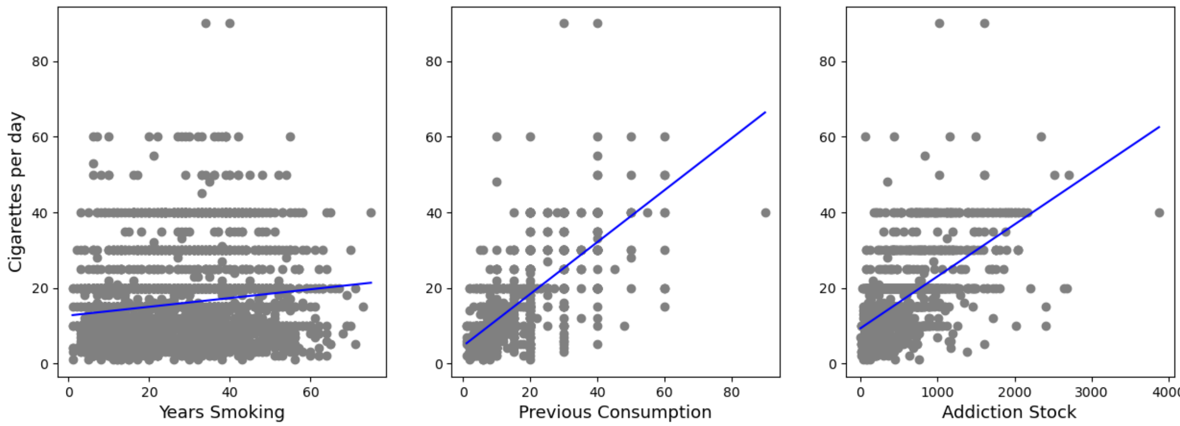


Figure B.1.1. Determinants of Consumption Intensity

	(1)	(2)	(3)	(1)	(2)
ϵ	0.052	-0.731	-0.142		
	(0.006)	(0.027)	(0.035)		
dc				1.510	1.266
				(0.098)	(0.060)
R^2	0.000	0.632	0.632	0.538	0.699
N	326376	326376	326376	204	193
FE	No	Yes	Yes	No	No
IV-FS -	-	-	-	-	

Table B.1.2. Elasticity and Pass-Through Regressions

	Own-Price	Agg. Market
Baseline Estimates	-0.853	-0.346
Prev. Literature	[-1.35, -0.64]	[-0.5, -0.15]

Note: Median elasticity in previous literature refers to Ciliberto and Kuminoff (2010); Liu et al. (2015) and Tuchman (2019). Evans and Farrely (1998) reported the aggregate elasticity range.

Table B.1.3. Demand Elasticity

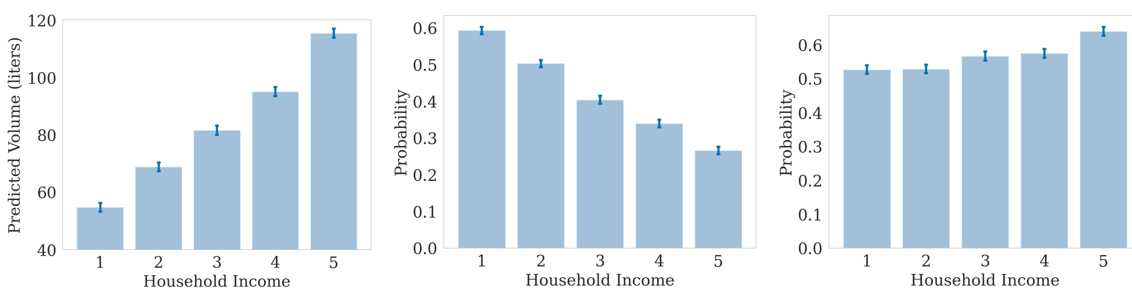
Appendix C

Appendix to Chapter Three

C.1 Appendix to Section 3.2

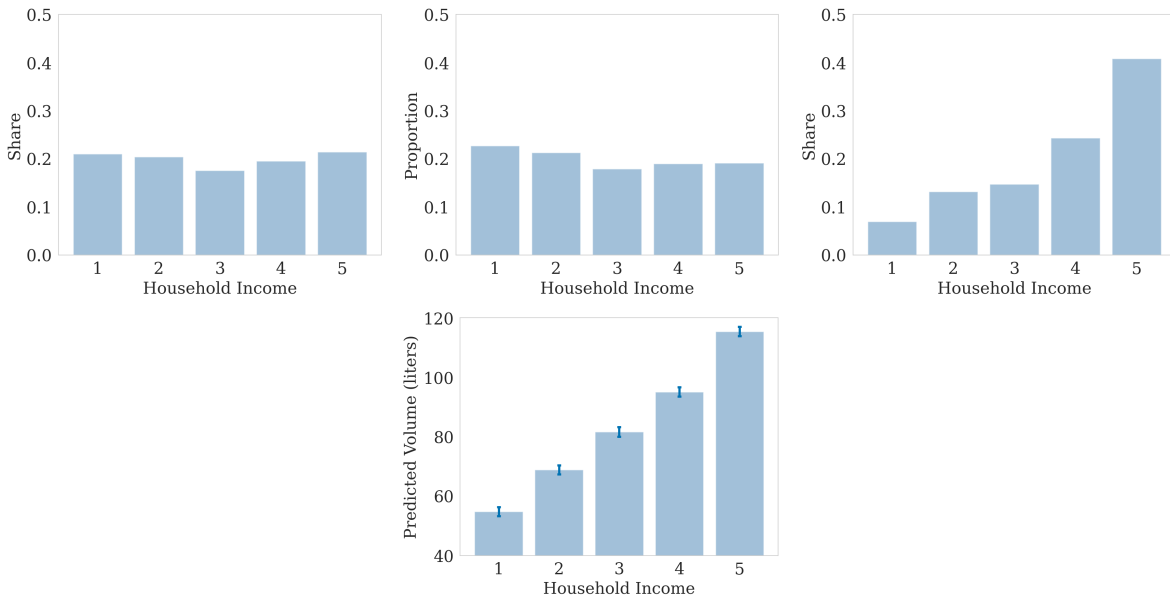
C.1.1 Consumption Patterns by Income Group

Figures C.2, C.1 and C.3 summarize gasoline consumption patterns of Argentinan households based on their income. Consumers of gasoline are uniformly distributed across income groups However, households of differnt income groups show different consumption patters. First, richer households consume more gasoline. In particular, households in the 5th quintile double the consumption of households in the first quintile. Second, high income households consume more premium gasoline. Finally, high-income households also consume more expensive regular and premium gasoline.



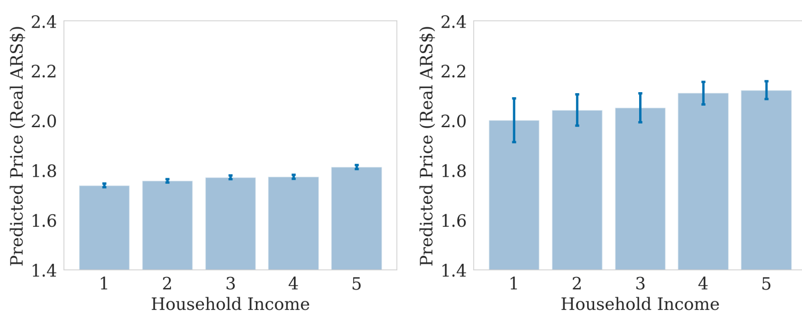
Note: Note: This figure displays various consumption patterns segmented by household income level. Panel (a) shows the predicted volume of gasoline consumed, with the y-axis indicating the volume in liters. Panel (b) presents the probability of owning a motorcycle across different income levels. Panel (c) illustrates the probability of traveling more than 50km per week. In all panels, the x-axis categorizes household income from 1 (lowest) to 5 (highest)

Figure C.1. Consumption patterns by income group: quantities



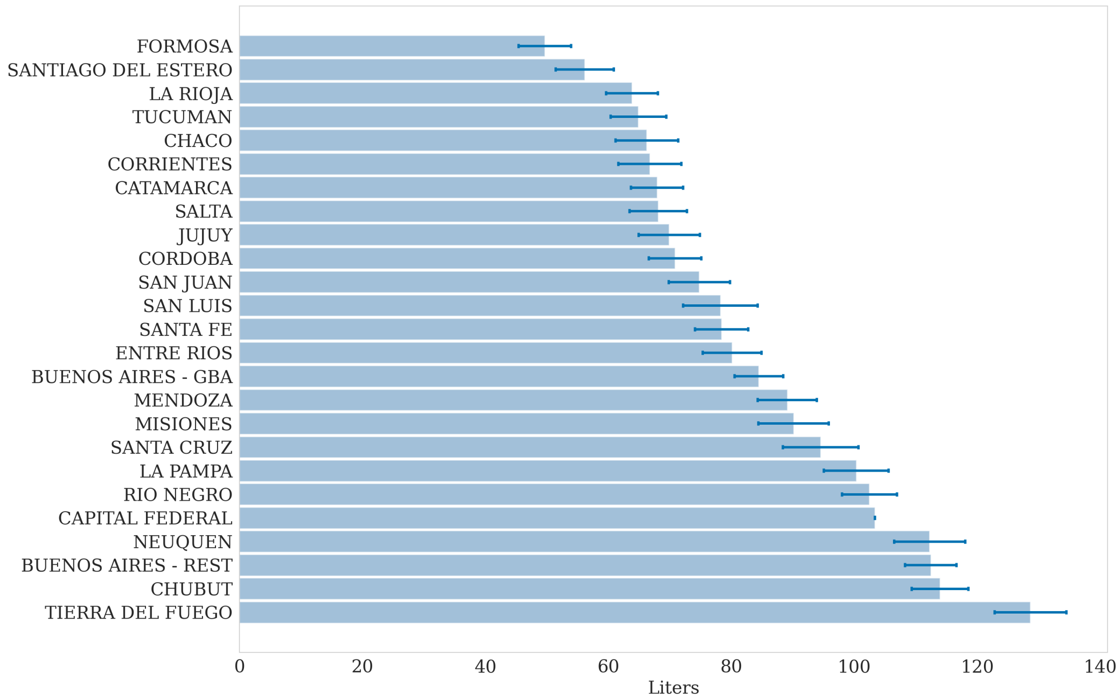
Note: Note: This figure illustrates consumption patterns of gasoline by household income. Panel (a) shows the distribution of all gasoline consumers across different income levels. Panels (b) and (c) depict the distribution specifically for consumers of regular and premium gasoline, respectively. Panel (d) presents the predicted volume of gasoline consumed, segmented by household income. The x-axis represents household income levels categorized from 1 (lowest) to 5(highest).

Figure C.2. Consumption patterns by income group and gasoline Type: quantities



Note: Note: This figure displays the average price paid for gasoline, differentiated by product type and consumer income level. Panel (a) depicts the mean price for regular gasoline, while Panel (b) shows the mean price for premium gasoline. The y-axis represents the predicted price per liter in ARS$, adjusted for location. In both panels, the x-axis categorizes household income from 1 (lowest) to 5 (highest), illustrating the relationship between income level and the prices paid for different types of gasoline. These predictions control for the geographic location of consumers.

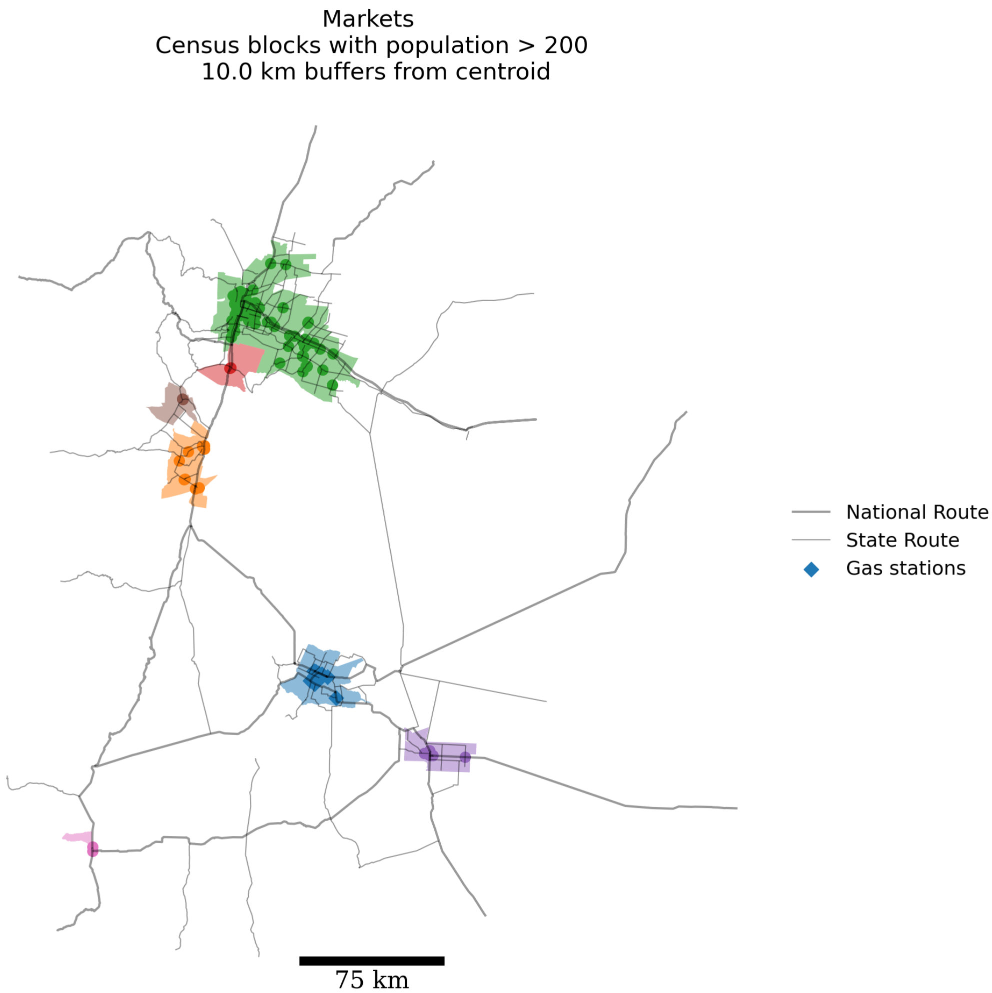
Figure C.3. Consumption patterns by income group: average price paid



Note: Note: Figure 14 presents the predicted gasoline consumption by province, with the quantities adjusted for differences in income levels. The y-axis lists the provinces in descending order of consumption, while the x-axis shows the volume of gasoline in liters. This analysis controls for income, allowing for a comparison of consumption patterns across provinces that is not influenced by income disparities. The data provides insights into regional variations in gasoline usage, which can inform targeted economic and environmental policies.

Figure C.4. Consumption patterns by province

C.1.2 Market definition



Note: Note: This figure shows the markets located in the province of Mendoza using our market definition algorithm. The colored dots represent gasoline stations, and the colored areas represent census blocks. Census blocks and stations of the same color belong to the same market.

Figure C.5. Market definition example - Mendoza

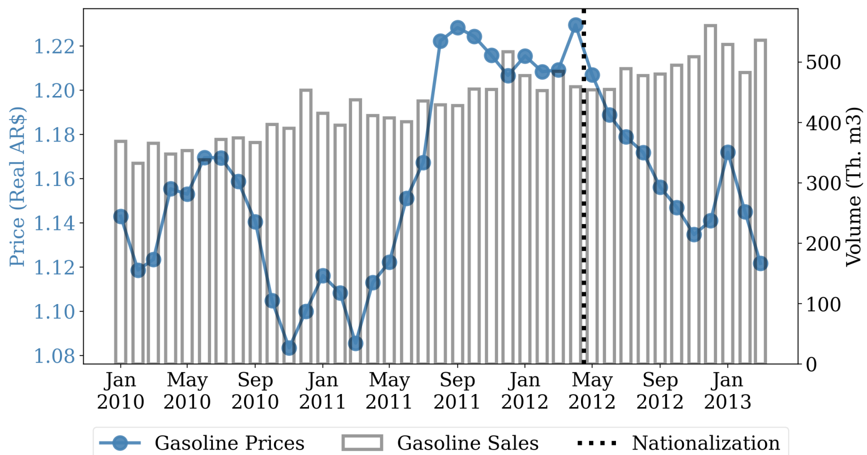
	p10	**p25**	**p50**	**p75**	**p90**
Market Size					
Population	5,942	11,057	23,754	48,037	112,508
# Stations	2	2	4	6	11
Volume - All Type	158	226	413	997	2,389
Market Shares					
Premium	19%	20%	25%	28%	33%
YPF	40%	51%	62%	76%	94%
Prices					
Regular - All	1.64	1.75	1.78	1.84	1.89
Regular - YPF	1.64	1.72	1.75	1.75	1.77
Premium - All	1.94	2.06	2.08	2.11	2.15
Premium - YPF	1.94	2.06	2.07	2.07	2.09
# Markets per Province	2	4	7	11	42

Note: Note: This table presents summary statistics for our sample. *Premium* represents the market share of all premium products. *YPF* represents the market shares for all YPF products. Prices are expressed in CPI-adjusted pesos and include taxes.

Table C.1. Summary statistics

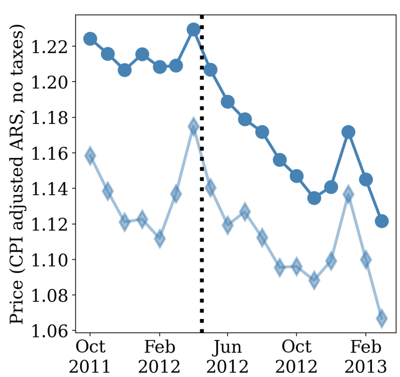
C.2 Appendix to Section 3.3

C.2.1 Appendix to fact 1



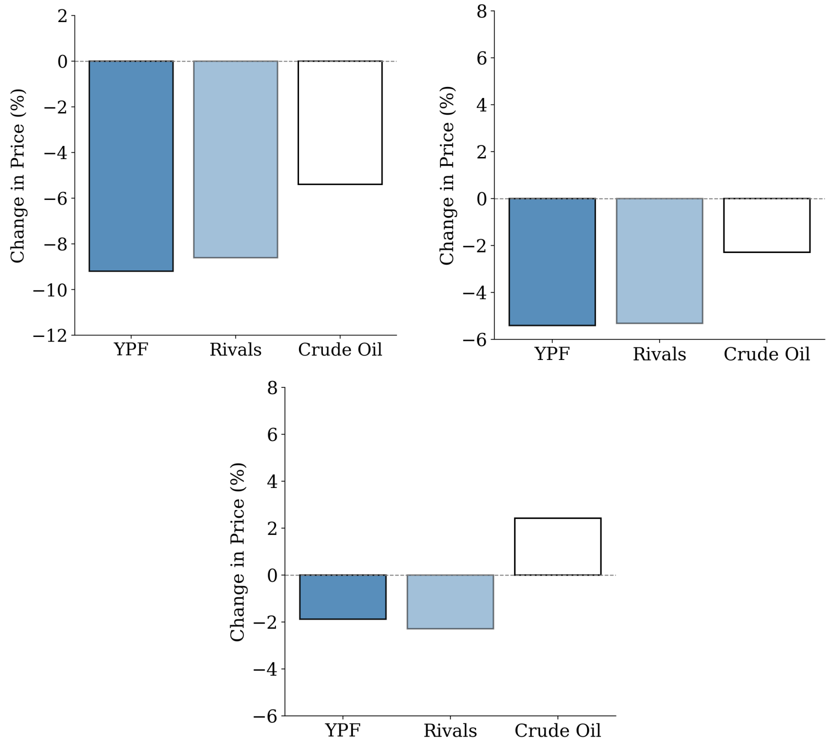
Note: Note: This figure displays the evolution of prices and gasoline sales for the period Jan-2010 to Feb-2013. The dotted line represents the date of the nationalization. Prices are expressed in CPI-adjusted pesos and do not include federal taxes

Figure C.6. Evolution of gasoline prices and sales



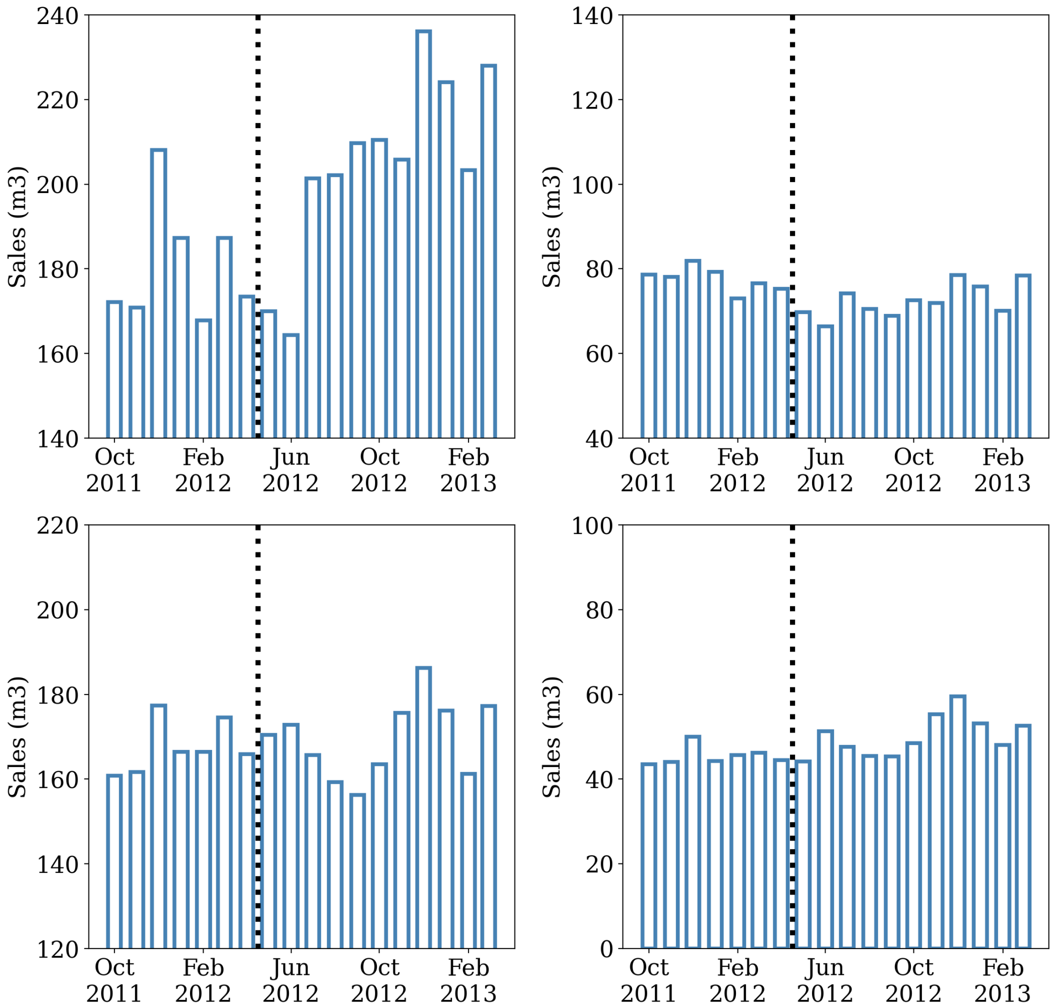
Note: Note: This figure displays the evolution of gasoline prices for the period Oct-2011 to Feb-2013. The dotted line represents the date of the nationalization. The dark blue line represent gasoline prices for all gasoline stations in the country. The light blue line represents the evolution of YPF's prices.

Figure C.7. Evolution of gasoline prices: YPF vs. other brands



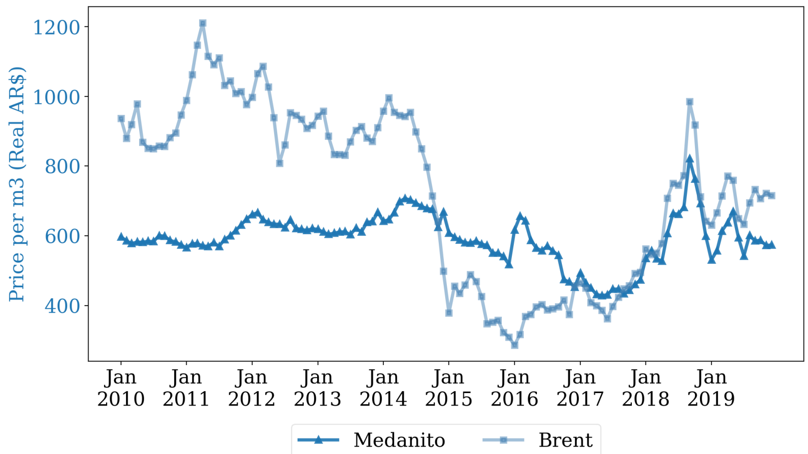
Note: Note: This graph shows the change in YPF gasoline prices, non-YPF gasoline prices, and local Crude-Oil prices (Medanito). All prices are expressed in CPI adjusted pesos per liter and do not include taxes. Figure (a) compares the prices during the last month of our sample (February 2013) vs. the last month before nationalization (April 2012). Figure (b) compares the average prices of the post-nationalization period (May 2012 to February 2013) vs. the last month before nationalization (April 2012). Figure (c) compares average prices in the pre-nationalization period (January 2010 to December 2011) to the post-nationalization period (May 2012 to Feb 2013)

Figure C.8. Change in gasoline prices vs. crude oil prices



Note: Note: This figure displays the evolution of gasoline sales for the period Oct-2011 to Feb-2013 by gasoline product. The dotted line represents the date of the nationalization.

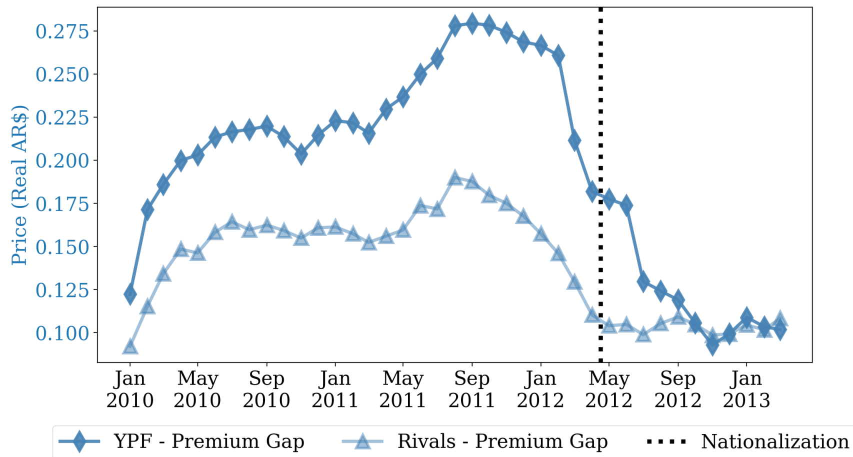
Figure C.9. Evolution of gasoline sales by product and brand



Note: Note: This figure displays the evolution of local (*Medanito*) and international ()*Brent*) crude oil prices.

Figure C.10. Evolution of crude oil prices - local vs international

C.2.2 Appendix to fact 2



Note: Note: This figure displays the difference between premium and regular gasoline for YPF and non-YPF gasoline stations. Prices are expressed in CPI-adjusted pesos and do not include federal taxes.

Figure C.11. Evolution of gasoline prices. Premium vs. regular gasoline

	(1)	(2)	(3)
Intercept	1.102***	1.102***	1.115***
	(0.002)	(0.002)	(0.003)
Middle Income HH	0.026***	0.026***	
	(0.002)	(0.002)	
High Income HH	0.022***	0.022***	
	(0.002)	(0.002)	
Post × Middle Income	-0.014***	-0.014***	
	(0.004)	(0.004)	
Post × High Income	-0.021***	-0.021***	
	(0.004)	(0.004)	
YPF Market Share			0.011**
			(0.005)
Post × YPF Market Share			-0.021**
			(0.009)
Time FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
R^2	0.07	0.07	0.07
Obs	68058	68058	68058

Dependent variable: Price per liter without federal taxes. Unit: Real AR$ (Oct - 2005)

Sample period Jan - 2010 to March-2013

Note: *p<0.1, **p<0.05, ***p<0.01.

Table C.2. Regression results. Change in YPF relative prices after the nationalization

	(1)	(2)	(3)	(4)
Intercept	1.122***	1.132***	1.122***	1.140***
	(0.000)	(0.000)	(0.001)	(0.001)
Post × Premium		-0.105***		-0.105***
		(0.001)		(0.001)
Post × Middle Income	-0.014***			-0.013***
	(0.002)			(0.002)
Post × High Income	-0.021***			-0.019***
	(0.002)			(0.002)
Post × YPF Market Share			-0.021***	-0.031***
			(0.004)	(0.004)
Time FE	Yes	Yes	Yes	Yes
Province FE	No	No	No	Yes
Station-Prod FE	Yes	Yes	Yes	No
R^2	0.79	0.81	0.79	0.81
Obs	68058	68058	68058	68058

Dependent variable: Price per liter without federal taxes. Unit: Real AR$ (Oct - 2005)

Sample period Jan - 2010 to March-2013

Note: *p<0.1, **p<0.05, ***p<0.01.

Table C.3. Regression results. Change in YPF relative prices after the nationalization

C.2.3 Appendix to fact 3

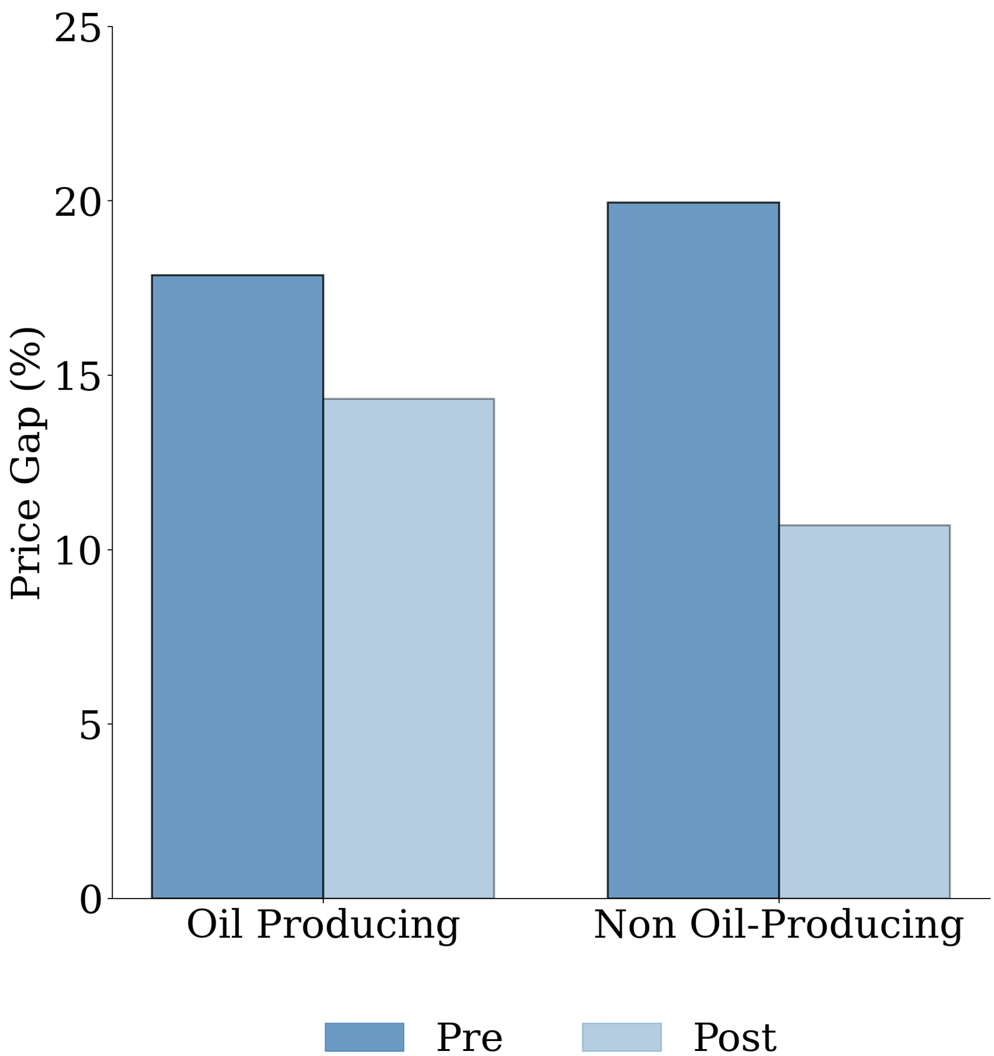


Figure C.12. Difference between YPF premium and regular gasoline. By province type

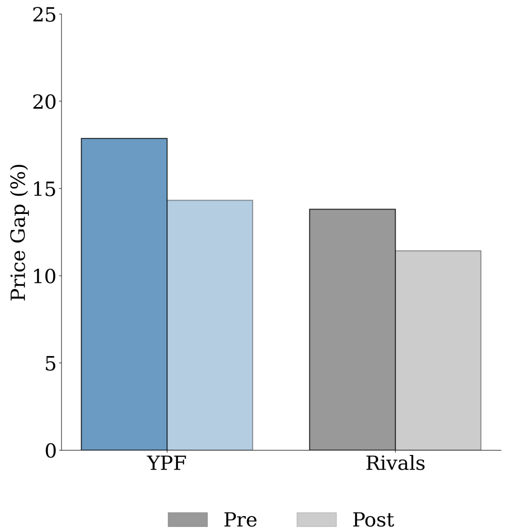


Figure C.13. Difference between premium and regular gasoline. YPF vs other brands

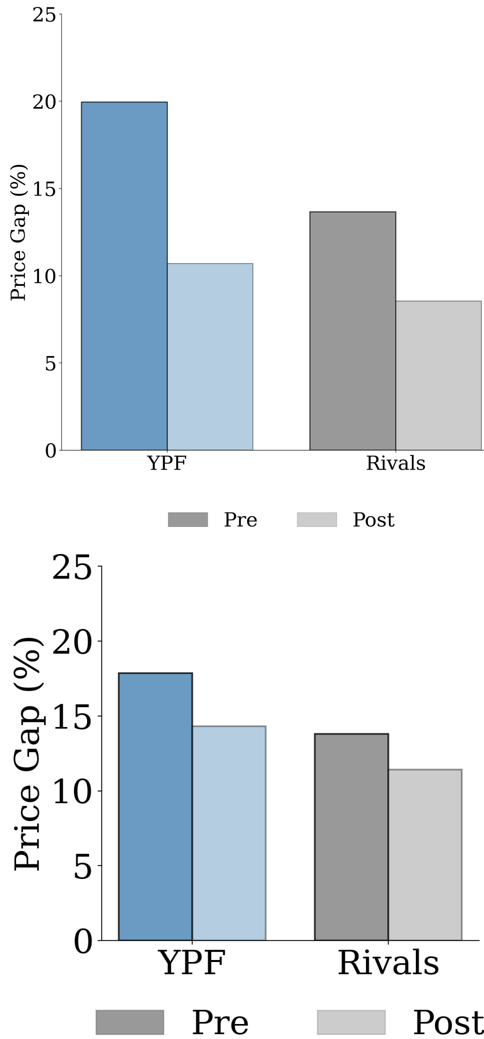


Figure C.14. Difference between premium and regular gasoline. YPF vs other brands

	All		Oil-Producing	
	Reg	Prem	Reg	Prem
Intercept	1.009***	1.206***	1.008***	1.203***
	(0.002)	(0.002)	(0.004)	(0.006)
Middle Income HH	0.021***	0.026***	0.009	0.003
	(0.002)	(0.002)	(0.006)	(0.007)
High Income HH	0.017***	0.018***	0.001	-0.001
	(0.002)	(0.003)	(0.006)	(0.007)
Post × Middle Income	-0.010***	-0.013***	0.014	0.024*
	(0.004)	(0.004)	(0.011)	(0.013)
Post × High Income	-0.018***	-0.017***	0.014	0.034***
	(0.004)	(0.005)	(0.011)	(0.013)
Time FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.17	0.18	0.16	0.28
Obs	35188	32870	5282	4750

Dependent variable: Price per liter without federal taxes. Unit: Real AR$ (Oct - 2005)

Sample period Jan - 2010 to March-2013

Note: *p<0.1, **p<0.05, ***p<0.01.

Table C.4. Regression results. Change in YPF relative prices after the nationalization

	(1)	(2)
Intercept	1.022***	1.026***
	(0.001)	(0.001)
Premium Gasoline	0.227***	0.226***
	(0.001)	(0.001)
Post × Premium	-0.105***	-0.108***
	(0.002)	(0.002)
Post × Oil-Producing		-0.082***
		(0.003)
Premium × Oil-Producing		0.004**
		(0.002)
Post × Premium × Oil-Producing		0.020***
		(0.005)
Time FE	Yes	Yes
Station FE	Yes	Yes
R^2	0.45	0.46
Obs	68058	68058

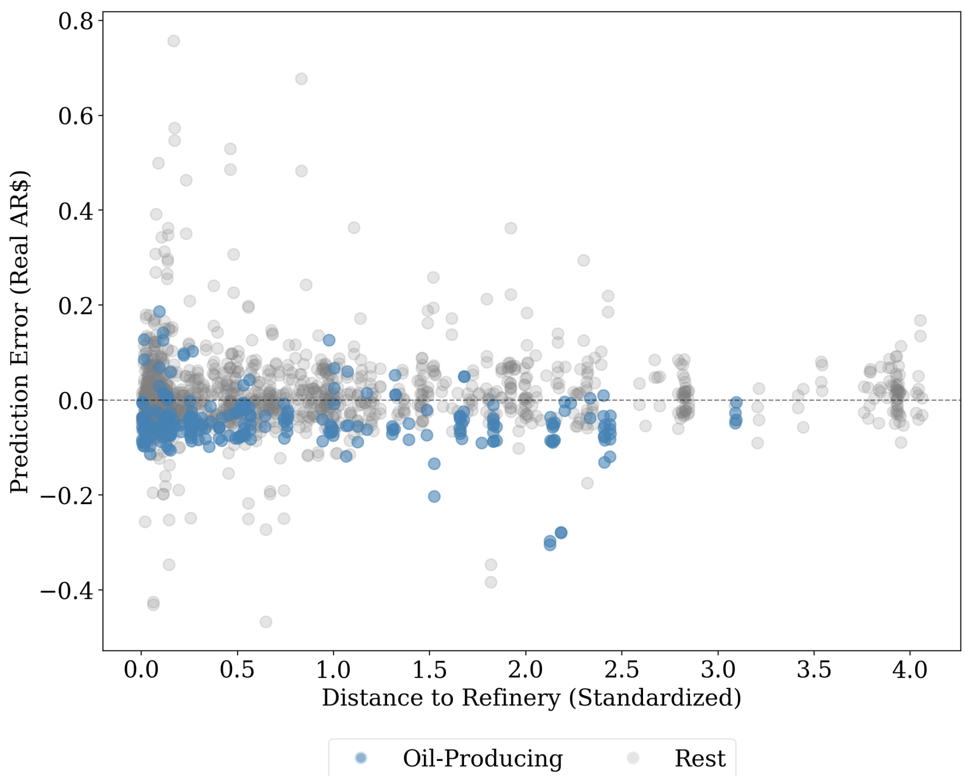
Dependent variable: Price per liter without federal taxes. Unit: Real AR$ (Oct - 2005)

Sample period Jan - 2010 to March-2013

Note: *p<0.1, **p<0.05, ***p<0.01.

Table C.5. Regression results. Change in YPF relative prices after the nationalization

C.2.4 Price changes and distance to refineries



Note: Note: This graph shows the relationship between the effects of the nationalization and distance to refineries. We regress prices on time and station-product fixed-effects, plus interactions between the post-nationalization period and gasoline type. We also include interactions between the nationalization period and household income levels (Refer to column 4 on Table C.3 for results). We use that specification to compute predicted prices in the post-nationalization period. We compute prediction errors by taking the difference between observed and predicted prices. We plot predictive errors on the distance to the closest YPF refinery. For visualization convenience, we present the results for December 2012.

Figure C.15. Change in YPF prices as a function of distance to refineries

	(1)
Intercept	1.140***
	(0.001)
Post × Middle Income	-0.010***
	(0.002)
Post × High Income	-0.016***
	(0.002)
Post × Distance to Refinery	0.006***
	(0.001)
Post × YPF Market Share	-0.039***
	(0.004)
Time FE	Yes
Station-Product-FE	Yes
Province FE	No
R^2	0.81
Obs	68058

Dependent variable: Price per liter without federal taxes. Unit: Real AR$ (Oct - 2005)

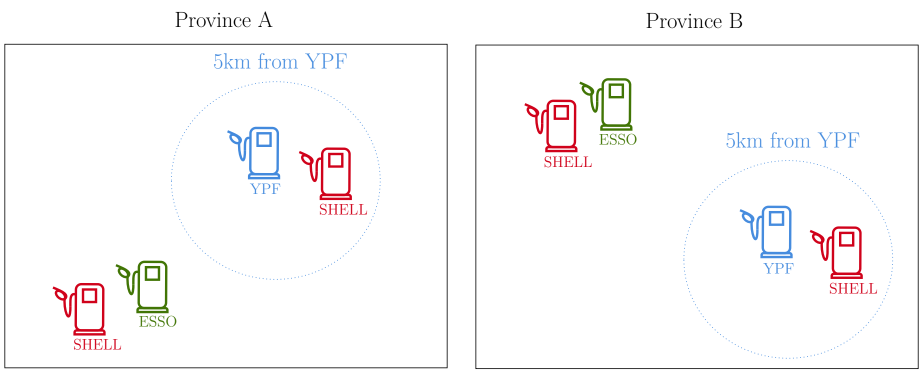
Sample period Jan - 2010 to March-2013

Note: *p<0.1, **p<0.05, ***p<0.01.

Table C.6. Regression results. Change in YPF relative prices after the nationalization

C.2.5 Difference in Differences Design

We examine whether the lower prices of YPF in oil-producing provinces were not a result of a deliberated policy by YPF but a response to a reduction in costs and gasoline demand across all stations in those provinces. The ideal experiment would compare the observed YPF prices after the nationalization with those that a counterfactual *profit-maximizing* YPF would have charged under the same demand and supply conditions. This direct comparison is unfeasible as data on the prices that YPF would have charged after the nationalization does not exist. In order to overcome this challenge, we exploit quasi-experimental variation generated by the fact that before the nationalization, some geographic areas were exposed to YPF competition while others were not. Figure C.16 illustrates our empirical strategy



Note: Note: This figures illustrates our empirical strategy

Figure C.16. Empirical strategy

We regress non-YPF prices (e.g., Shell, ESSO) on product-station fixed effects, brand and month fixed effects, month and region fixed effects, interactions between a post-nationalization dummy, and whether the gasoline station was exposed to YPF competition. By including station-product fixed effects, we capture differences in price levels of different stations before the nationalization. By including brands and months fixed effects, we capture brand-specific pricing trends (for instance, as a consequence of changes in production costs or willingness to pay for products of specific brands). Finally, by including region and month fixed effects, we control for demand and cost shocks common to all gasoline stations within a region. So conceptually, this analysis compares the evolution of prices of a rival station close to a YPF with another station of the same brand in the same region but not competing against a YPF. Under the assumptions of parallel trends in the costs of stations of similar brands and the costs of stations in the same province, the coefficient of interest captures the effect of being close to a YPF station on rivals' markups.[1]. Equation C.16 presents our main specification

$$price_{i,t} = \alpha_i + \beta_{t,brand(i)} + \gamma_{t,region(i)} + \tau \times \mathbf{1}\{t \geq t_{\text{nationalization}}\} \times \mathbf{1}\{\text{YPF at distance km}\}$$

On average, competitors in shareholder provinces exposed to YPF competition set their markups 6% lower post-nationalization compared to similar stations unexposed to YPF competition. Markups of these two groups trended similarly before the nationalization. Effects are more prominent for regular than for premium gasoline. Results are robust to alternative definitions of treated and control groups and to estimate the effects of the nationalization using the BJS estimator. Figure C.17 presents event-study plots for regular and premium gasoline.

This analysis indicates that exposure to YPF competition in shareholder provinces after the nationalization was associated with lower markups. It suggests that what drives lower prices in shareholder provinces is not a demand or cost shock that affects all provinces but exposure to YPF competition.

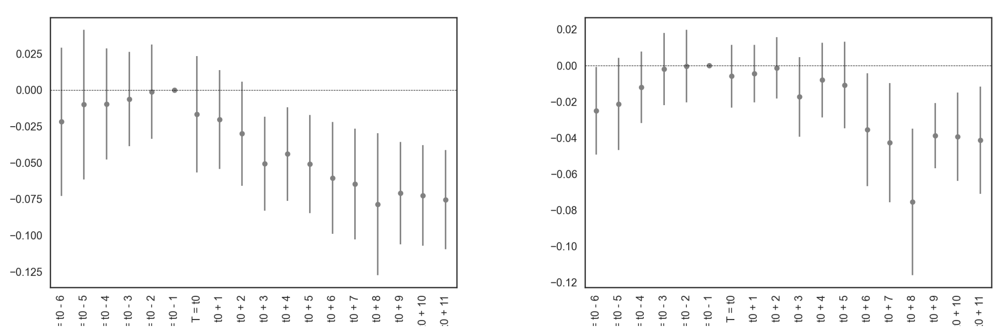


Figure C.17. Effect of YPF proximity on rival's prices - oil-producing provinces

[1]Incude derivation

	# Stations		Prices (median)		Volume (median)	
	Control	Treatment	Control	Treatment	Control	Treatment
Shell	46	459	2.01	1.94	55.18	105.46
Esso	31	336	1.97	1.87	51.86	97.85
Petrobras	13	198	2.01	1.88	67.78	103.87
Other Brands	41	272	2.04	1.98	38.27	62.81
Unbranded	74	202	2.10	2.07	15.26	18.00

Table C.7. Summary statistics - regular gasoline

C.3 Appendix to Section 3.5

C.3.1 Demand Results

	Coefficient	S.E.
Constant	-5.871***	(0.027)
Premium	2.052***	(0.018)
Unbranded	-0.929***	(0.038)
Small Brands	-1.219***	(0.038)
YPF	-0.057**	(0.029)
Shell	-0.156***	(0.032)
Petrobras	2.090***	(0.038)
Market size (Th)	-0.167***	(0.002)
R-squared Adj.	0.095	
Median Elasticity	-3.52	
Mkt Size - p10	264	
Mkt Size - p50	1,361	
Mkt Size - p90	9,049	
Note: *p<0.05, **p<0.01, ***p<0.001		

Note: Note: This table shows the results of regressing own-price elasticities on a constant, station's brand dummy variables, whether the product is regular or premium gasoline, and market size. The brand ESSO was left as a control group.

Table C.8. Own price elasticities - regression results

Own Price Elasticity		**Outside Option Elasticity**	
Median	Houde (2012)	Median	Benchmarks
-3.52	-10	-0.53	-0.37

Table C.9. Benchmarking

	Coefficient	S.E.
Constant	0.032***	(0.003)
Same Quality	0.096***	(0.004)
Same Brand	0.046***	(0.004)
Same Station	0.305***	(0.010)
Closest Rival	0.319***	(0.007)
Closest Rival #2	0.257***	(0.007)
Closest Rival #3	0.195***	(0.008)
Closest Rival #5	0.089***	(0.009)
Closest Rival #10	0.001	(0.011)
R-squared Adj.	0.071	
Mean Elasticity – Inside Goods	3.47	
Median Market Shares (%)	0.89%	
Note: *p<0.05, **p<0.01, ***p<0.001		
Note 2: Mean Elasticity – Inside Goods is average sum of cross price elasticities		

Table C.10. Cross price elasticities - regression results

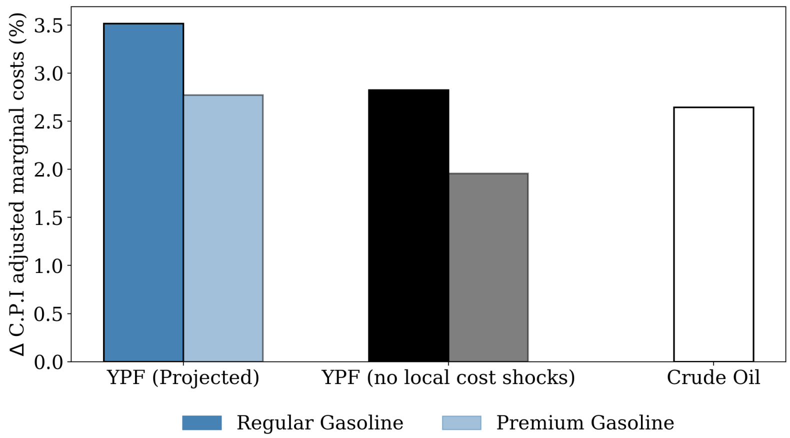
C.3.2 Marginal Costs Results

	Marginal Costs	S.E.
Premium	0.031**	(0.002)
YPF	-0.249**	(0.003)
SHELL	-0.016**	(0.003)
PETROBRAS	0.010*	(0.004)
UNBRANDED	0.092**	(0.005)
Distance (100km)	0.004**	(0.001)
Crude Oil Price (AR$ per liter)	0.106**	(0.006)
Province FE	Yes	
Time FE	No	
Obs	70315	
Adj. R^2	0.680	
F-stat	4974.386	

Sample period Jan - 2010 to Sept -2011

Note: Note: This table shows the results of regressing marginal costs on a constant, station's brand dummy variables, whether the product is regular or premium gasoline, and market size. The brand ESSO was left as a control group.

Table C.11. Marginal costs - regression results



Note: Note: This figure shows the evolution of the weighted avarage marginal costs for different firms and products. It compares the post-nationalization period with the whole pre-nationalization sample period.

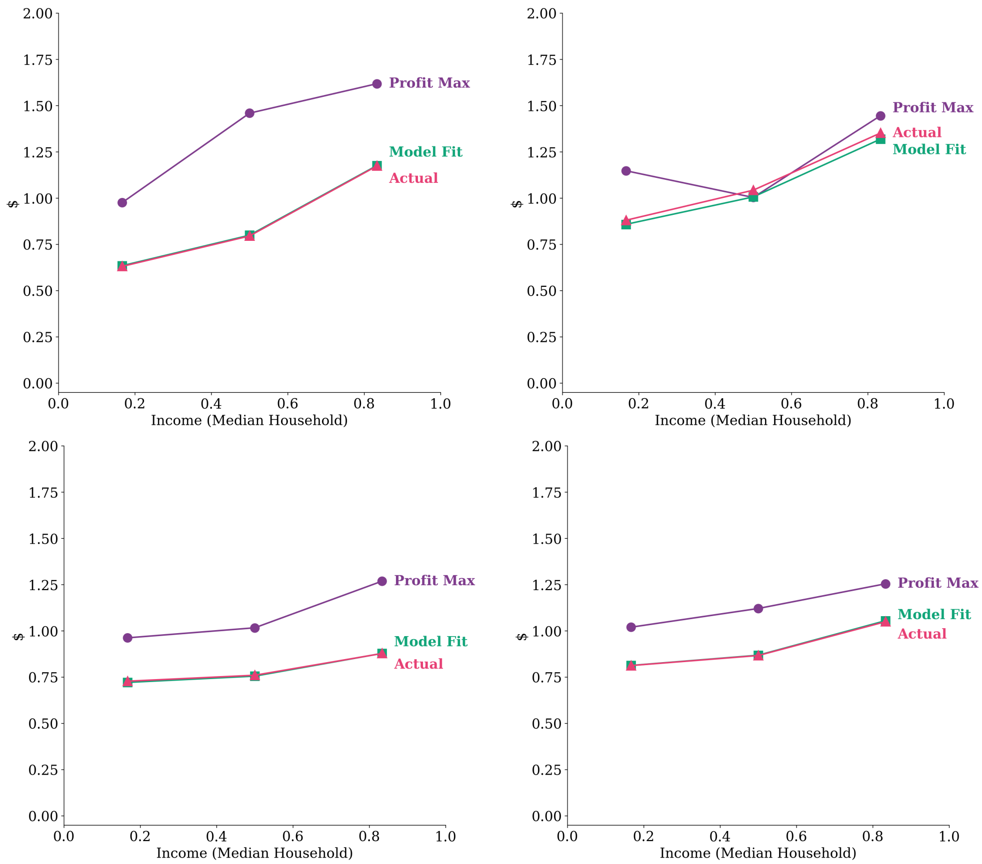
Figure C.18. Evolution of marginal costs of gasoline by product type

Parameter	Point Estimate	Confidence Interval	Description
$\lambda^{\text{non-oil producing}, L}$	-0.25	(-0.56, 0.06)	Low income consumers in non-oil producing provinces
$\lambda^{\text{oil producing}, L}$	0.72	(0.33, 1.10)	Low income consumers in oil producing provinces
$\lambda^{\text{non-oil producing}, M}$	0.27	(0.02, 0.51)	Middle income consumers in non-oil producing provinces
$\lambda^{\text{oil producing}, M}$	0.22	(0.15, 0.30)	Middle income consumers in oil producing provinces
$\lambda^{\text{non-oil producing}, H}$	-0.09	(-0.26, 0.08)	High income consumers in non-oil producing provinces
$\lambda^{\text{oil producing}, H}$	0.03	(-0.01, 0.07)	High income consumers in oil producing provinces
κ	-0.01	(-0.12, 0.11)	Firms

Note: Note: This table present results of conduct parameters in our baseline specification. Confidence intervals are computed using the bootstrap distribution of the estimates, and adjusting critical values using Hall and Horowitz (1996)

Table C.12. Results - Main Specification

C.3.3 Model Fit - Relevance of Strutural Error in Markups



Note: Note: Subfigures (a) and (b) depict markups for regular and premium gasoline as a function of the median income of households within the census block of the station's location. The purple line illustrates the profit-maximizing case, while the pink line shows the actual markups YPF set, using our cost estimates. The additional case is the prediction of our model without using the estimated unobserved errors. (green line).

Figure C.19. Correlation between income and markups under different scenarios

C.4 Appendix: Markup Patterns

In order to rationalize our results, we compare the actual markups that YPF charged (based on our cost estimates) with (1) the expected markups that a profit-maximizing firm would have charged and (2) the markups that firms with different parametrizations would have charged. This exercise illustrates the discussion of subsection 3.5.3.

We did the following steps:

- For each gasoline station and using our cost estimates, we simulate prices under different objective function parameterizations. In particular, a profit-maximizing case, a case in which the government only internalizes the consumer surplus of low-income groups ($\lambda_L = 2$, in), a case in which the government only internalizes consumer surplus of middle-income groups ($\lambda_M = 0.5$), a case in which the government only internalize consumer surplus of high-income groups ($\lambda_H = 0.75$), and a case in which the government does not internalize consumer surplus of any group but puts a negative weight on rivals' profits ($\kappa < -0.4$).

- We match each gasoline station with the income level of the median household located in the very same census block -this allows us to classify stations with high-income or low-income neighborhoods based on observable characteristics-. We compute the average markups, conditioning on the station being located in a low-income, middle-income, or high-income location.

- Additionally, we match YPF's market shares in the market in which that station is located- this allows us to match stations with different levels of rivals' presence-. We compute the average markups, conditioning on the station being located in markets in which YPF has market shares lower than 33%, market shares between 33% and 66%, and market shares above 66%.

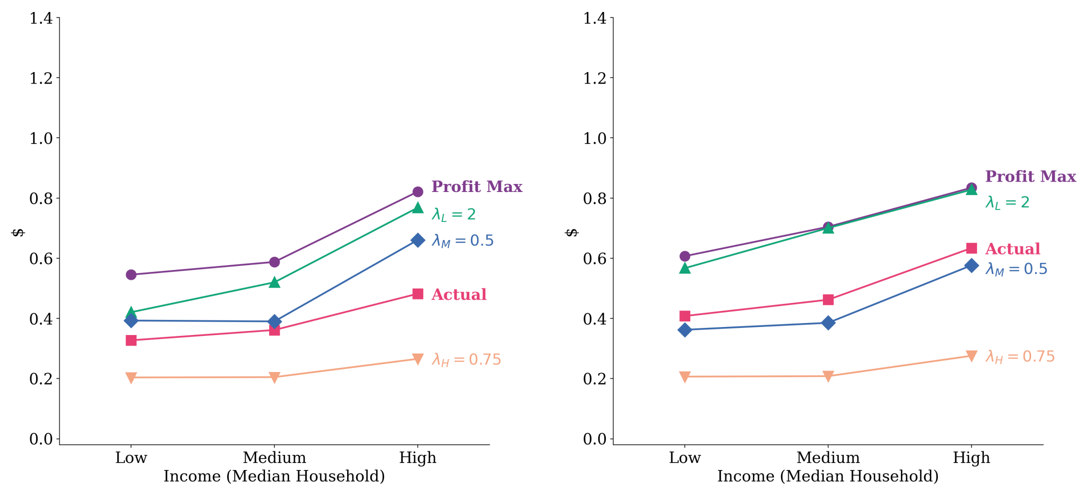
- For illustration purposes, we did the same exercise with markups that YPF charged based on our cost estimates.

Figure C.20 presents average markups for regular and premium gasoline, conditioning on the income level associated with the station's location, for non-shareholder provinces. First, note that different specifications generate different markups at different locations, being the profit-maximizing case the one in which markups are the highest purple line). In the profit-maximizing case, average markups are higher for both regular and premium gasoline in high-income locations. This pricing is consistent with YPF charging higher prices to more inelastic consumers. Also, note that in the full consumer surplus internalization case, the firm does marginal cost pricing, so all markups are equal to zero, and there is no price discrimination based on income level.

Four features of the data allow us to discriminate between different objective functions.

Markups of regular vs. premium gasoline at a given province or province type The first type of variation that allows us to disentangle different models is the difference in markups between regular and premium gasoline within a region. Since low-income consumers usually do not consume premium gasoline, a policy that internalizes consumer surplus of low-income consumers (green line) is associated with ”subsidies” on regular gasoline and almost no discounts on premium gasoline (we use the term subsidies to refer to any positive difference between profit-maximizing markups and the markups charged by the state-own enterprise). Note that a policy that targets high-income groups (orange line) generates similar subsidies for both premium and regular gasoline. Finally, a policy that targets middle-income groups is somehow in the middle (blue line)

Geografical correlation between markups and consumer's income level The second pattern in the data that aids identification is the geographical correlation between subsidies and consumer's income. A policy that targets low-income individuals (green line) charges relatively lower markups in low-income areas and relatively higher markups in high-income areas. This correlation gets more nuanced as we move from a policy that targets low-income individuals to a policy that targets middle-income individuals (blue line), and almost disappears in the case of a policy that targets high-income individuals (orange line). Since consumers are not perfectly segmented across the space, even a policy targeting low-income individuals will generate some subsidy in high-income areas. The more segmented income groups are across the space, the more informative the correlation between markups and income level will be. If consumers are perfectly overlapping across the space, then this variation will not be able to tell apart different models.



Note: *Note:* Subfigures (a) and (b) depict markups for regular and premium gasoline as a function of the median income of households within the census block of the station's location. The purple line illustrates the profit-maximizing case, while the pink line shows the actual markups YPF set, using our cost estimates. Additional cases presented are when the government internalizes the consumer surplus of only the low-income groups (green line), only the middle-income groups (blue line), or only the high-income groups (orange line).

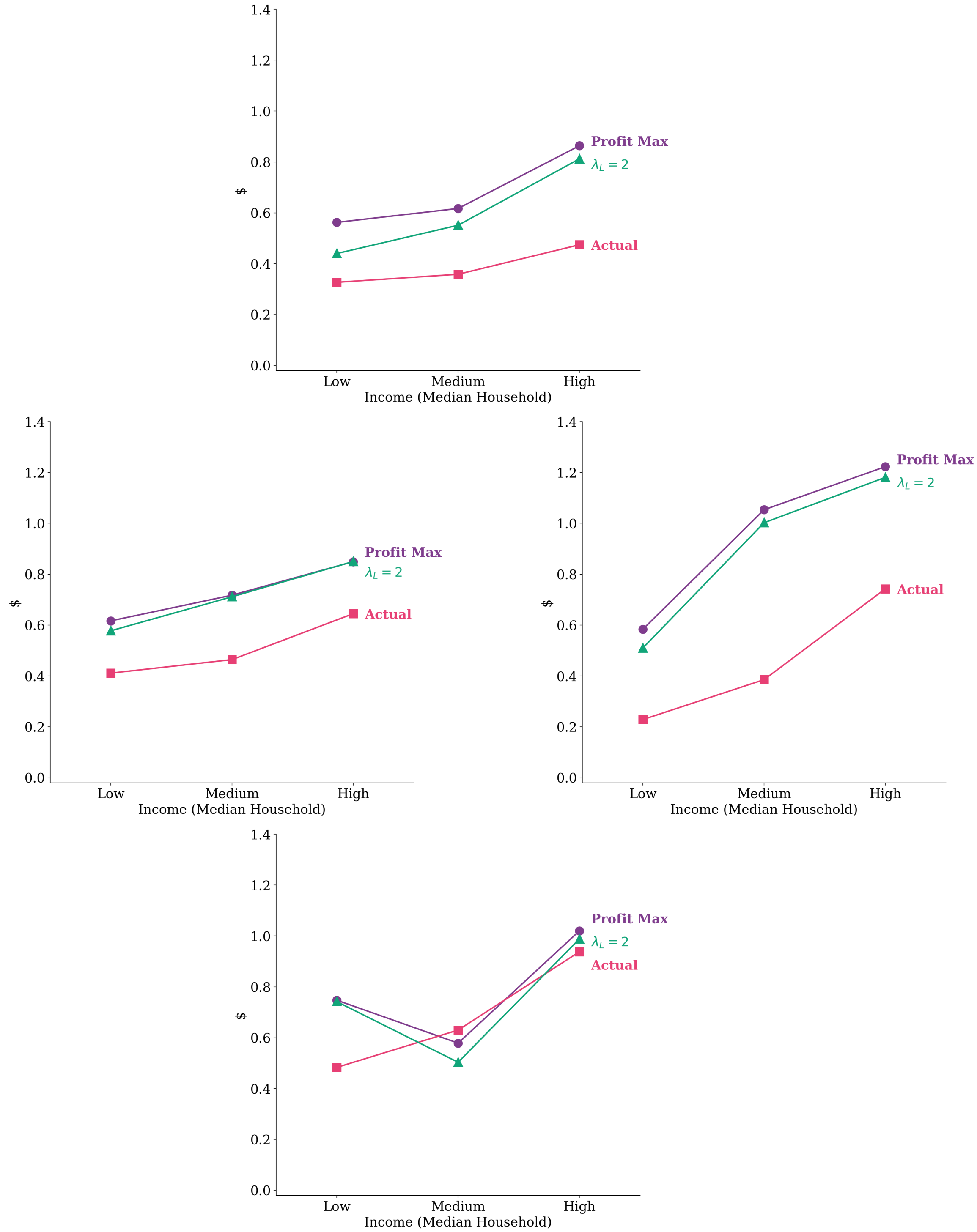
Figure C.20. Actual vs. simulated markups under different parameterizations: all provinces

Markups of gasoline products across provinces Differences patterns between shareholder and non-shareholder provinces in average subsidies to premium and regular gasoline and different patterns in the correlation between markups and consumer's location allow us to identify if the SOEs have different preferences for consumers in shareholder and non-shareholder provinces.

Figure C.21 presents average markups for regular and premium gasoline as a function of station's location income level for both non-shareholder provinces (top panel) and non-shareholder provinces (bottom panel). As in the previous graph, the purple line represents the profit-maximizing case. The pink line, represents the actual markups that YPF charged based on our cost estimates. Finally, we keep the line representing the case in which the government only internalizes the consumer surplus of low-income groups (green line).

Markup patterns are considerably different across both space and product when comparing shareholder and non-shareholder provinces. First, the subsidies on regular gasoline are considerably higher in shareholder provinces. In low-income areas, they are around 50% higher. In middle-income areas, the subsidies almost double those in non-shareholder provinces. Second, while in non-shareholder provinces, subsidies for regular gasoline are moderately higher than subsidies for premium gasoline, In shareholder provinces, the discount on premium gasoline is relatively small.

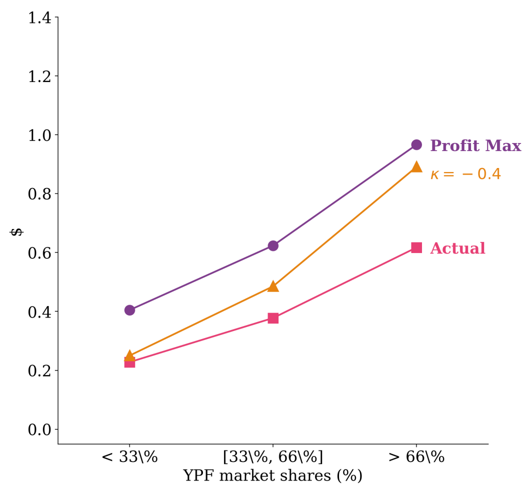
In shareholder provinces, the difference in subsidies between regular and premium gasoline allows us to point down a policy that targets low-income groups. Also, higher subsidies for regular gasoline in middle-income areas inform us about a policy that targets middle-income groups. In non-shareholder provinces, the amount of subsidies in premium gasoline and flatness in the correlation between subsidies and income level is inconsistent with targetting low-income populations. The difference in relative subsidies between regular and premium gasoline and the slope of the purple line (especially in premium gasoline) allows the model to distinguish between targetting middle income vs. targetting the richer groups.



Note: Note: Subfigures (a) to (d) depict markups for regular and premium gasoline as a function of the median income of households within the census block of the station's location. The purple line illustrates the profit-maximizing case, while the pink line shows the actual markups YPF set, using our cost estimates. The additional line represents the case in which the government internalizes the consumer surplus of the low-income groups (green line).

Figure C.21. Correlation between income and markups under different parameterizations

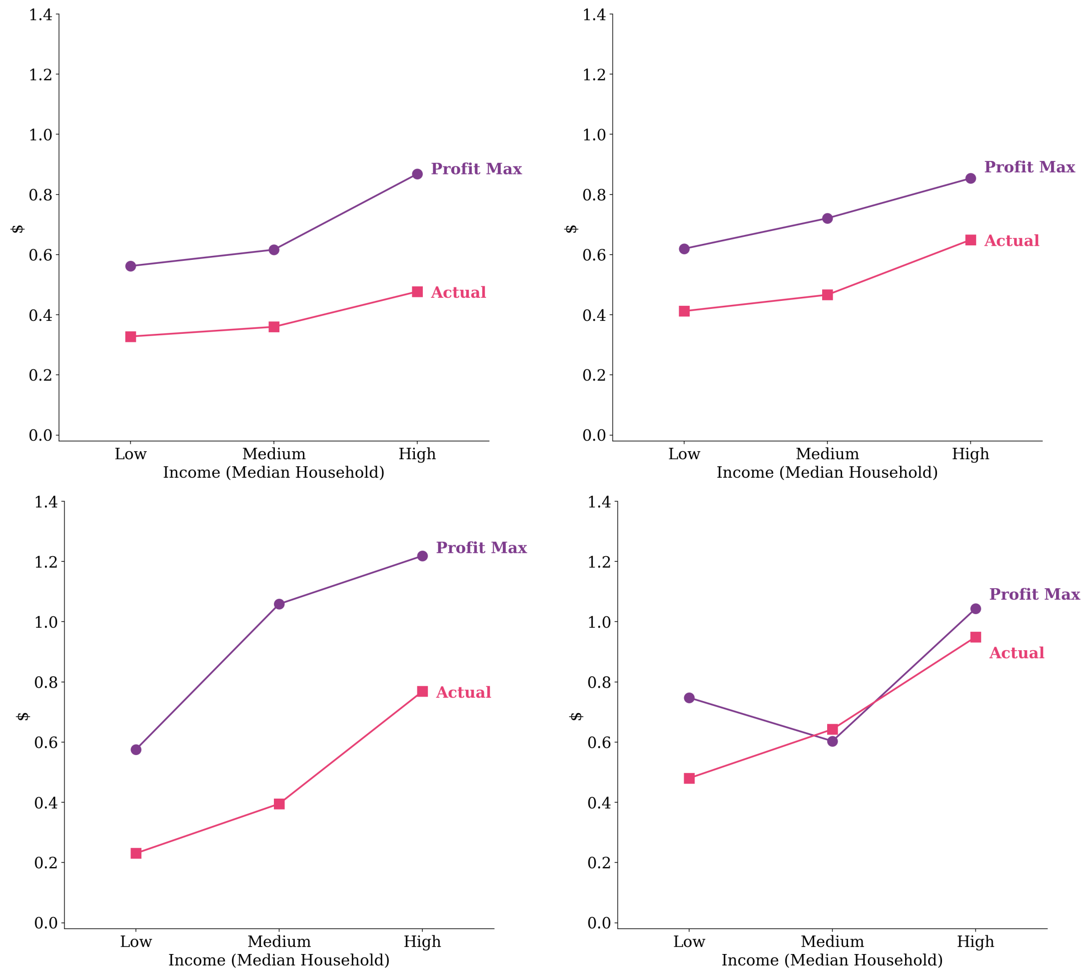
Correlation between markups and rival's relevance The last step in this argument is to distinguish lower markups due to the internalization of consumer surplus from lower markups due to the negative internalization of rival's profits. Figure C.22 presents average markups for all gasoline products, conditioning on YPF's market shares in the market in which the station is located. Note that a profit-maximizing firm would charge higher markups in more concentrated markets. Interestingly, the patterns generated by a firm that put negative weights on rival firms (orange line) are pretty different from a firm that put positive weight on consumers (blue line). The former charges relatively lower markups the more competition it faces (as if it were trying to kick rivals out of the market) and acts precisely as a profit-maximizing firm in markets where rivals are irrelevant. On the contrary, a firm that puts positive weights on consumers charges lower markups everywhere.



Note: Note: This figure depicts markups for all gasoline types as a function of YPF's market share for the station's corresponding market, during the year before nationalization. The purple line represents the profit-maximizing scenario, while the pink line shows YPF's actual markups based on our cost estimates. We also present a scenario where YPF negatively internalizes its rivals' profits (orange line).

Figure C.22. Actual vs. simulated markups under different parameterizations

C.5 Appendix: Estimation

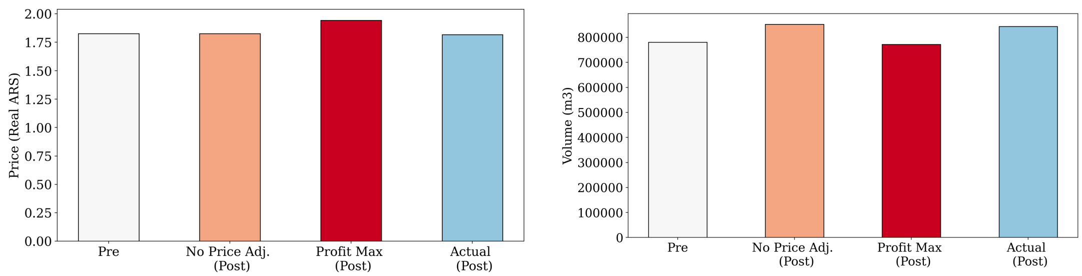


Note: Note: Subfigures (a) and (b) depict markups for regular and premium gasoline as a function of the median income of households within the census block of the station's location. The purple line illustrates the profit-maximizing case, while the pink line shows the actual markups YPF set, using our cost estimates.

Figure C.23. Correlation between income and markups under different parameterizations

C.6 Appendix to Section 3.6

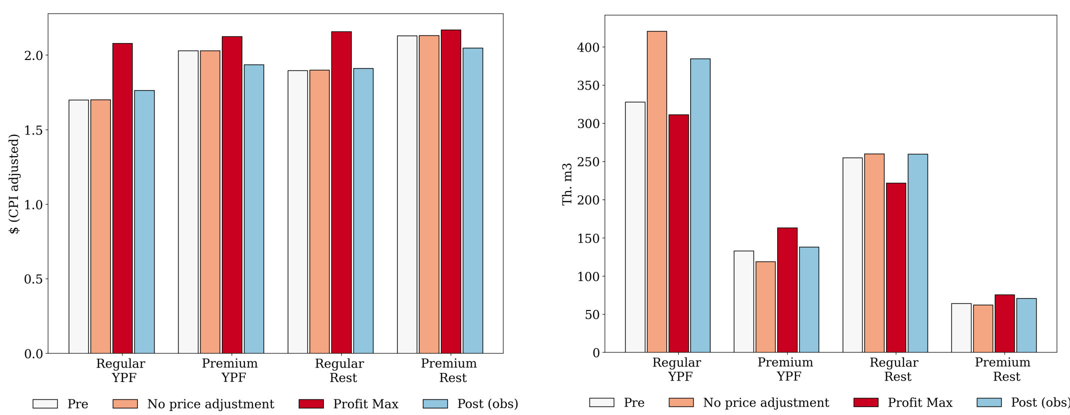
C.6.1 Effects on aggregate prices and sales



Note: Note: Figures (a) and (b) present prices and sales under different scenarios.

Figure C.24. Actual vs profit-maximizing prices and sales

C.6.2 Effects on prices and sales by brand and product type



Note: Note: Figures (a) and (b) present prices and under different scenarios for all provinces

C.6.3 Effects on Consumption by Product and Consumer Type

	Regular Gasoline			Premium Gasoline		
	Profit Max	Actual	*(%)*	Profit Max	Actual	*(%)*
Panel 1: Oil-Producing						
High Income	183	203	*11.0*	54	56	*3.6*
Middle Income	44	58	*30.7*	11	15	*40.4*
Low Income	21	27	*33.8*	4	2	*-56.7*
Panel 2: Other Provinces						
High Income	471	494	*5.0*	189	218	*15.2*
Middle Income	306	363	*18.6*	87	144	*66.8*
Low Income	129	125	*-2.4*	3	18	*532.3*
Panel 3: All Provinces						
High Income	654	697	*6.6*	243	274	*12.6*
Middle Income	350	421	*20.1*	98	160	*63.8*
Low Income	149	153	*2.6*	6	19	*202.9*

Table C.13. Effects by demographic group - all brands

	Regular Gasoline			Premium Gasoline		
	Profit Max	Actual	*(%)*	Profit Max	Actual	*(%)*
Panel 1: Oil-Producing						
High Income	112	129	*14.5*	37	40	*10.3*
Middle Income	25	37	*46.2*	7	11	*69.6*
Low Income	11	22	*103.7*	0	1	*171.8*
Panel 2: Other Provinces						
High Income	260	275	*5.8*	116	142	*22.3*
Middle Income	177	207	*17.2*	49	95	*92.2*
Low Income	84	87	*3.3*	1	13	*981.4*
Panel 3: All Provinces Provinces						
High Income	373	404	*8.4*	153	182	*19.4*
Middle Income	202	244	*20.8*	56	106	*89.5*
Low Income	95	109	*14.8*	2	14	*755.6*

Table C.14. Effects by demographic group - YPF

Effects on Markups

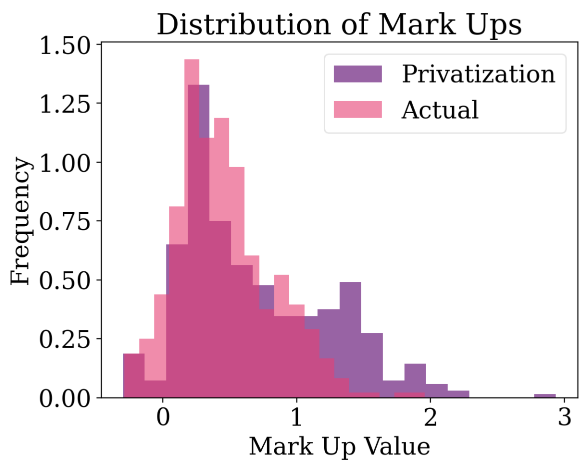


Figure C.26. Distribution of markups by income group - regular Gasoline

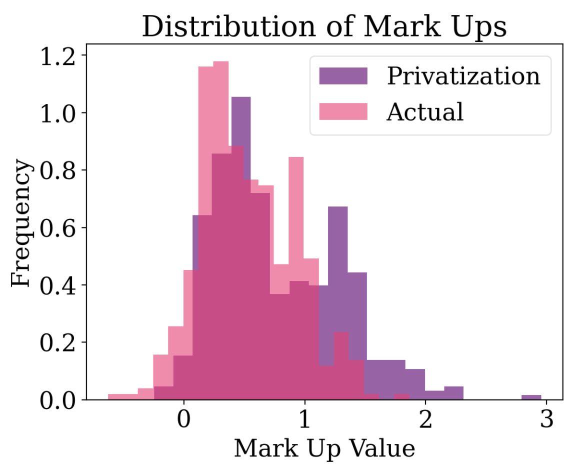


Figure C.27. Distribution of markups by income group - premium Gasoline

C.6.4 Summary Tables

	Actual	Privatization	Full CS	p = mc
Panel 1: Oil-Producing				
CS	25.1	21.5	40.0	45.3
Profits YPF	10.4	10.6	-0.0	0.0
Profits rest	4.2	4.8	3.0	0.0
Total Surplus	39.6	36.9	43.0	45.3
Panel 2: Other Provinces				
CS	98.8	88.6	138.5	156.9
Profits YPF	27.8	28.5	-0.0	0.0
Profits rest	13.9	15.7	10.3	0.0
Total Surplus	140.4	132.9	148.8	156.9
Panel 3: All Provinces				
CS	123.9	110.1	178.5	202.2
Profits YPF	38.1	39.2	-0.0	0.0
Profits rest	18.0	20.5	13.3	0.0
Total Surplus	180.0	169.8	191.8	202.2

Note: Note: Column 2 (*Privatization*) correspond to a counterfactual scenario in which YPF acts as a profit maximizing firm. Column 3 (*Full CS*) corresponds to a scenario in which YPF fully internalize consumer and producer surplus. Finally, the fourth column represent a scenaro in which all firms do marginal cost pricing.

Table C.15. Welfare Effects: nationalization vs alternative Scenarios

C.7 Appendix to Section 3.7

	Actual	Uniform Pricing	Uniform Mark-ups	Full CS
Panel 1: Oil-Producing				
CS	25.1	21.7	25.7	40.0
Profits YPF	10.4	10.0	9.8	-0.0
Profits rest	4.2	4.9	4.4	3.0
Total Surplus	39.6	36.6	39.9	43.0
Panel 2: Other Provinces				
CS	98.8	97.2	94.3	138.5
Profits YPF	27.8	26.7	26.2	-0.0
Profits rest	13.9	14.7	15.8	10.3
Total Surplus	140.4	138.6	136.3	148.8
Panel 3: All Provinces				
CS	123.9	118.9	120.0	178.5
Profits YPF	38.1	36.6	36.0	-0.0
Profits rest	18.0	19.6	20.2	13.3
Total Surplus	180.0	175.1	176.2	191.8

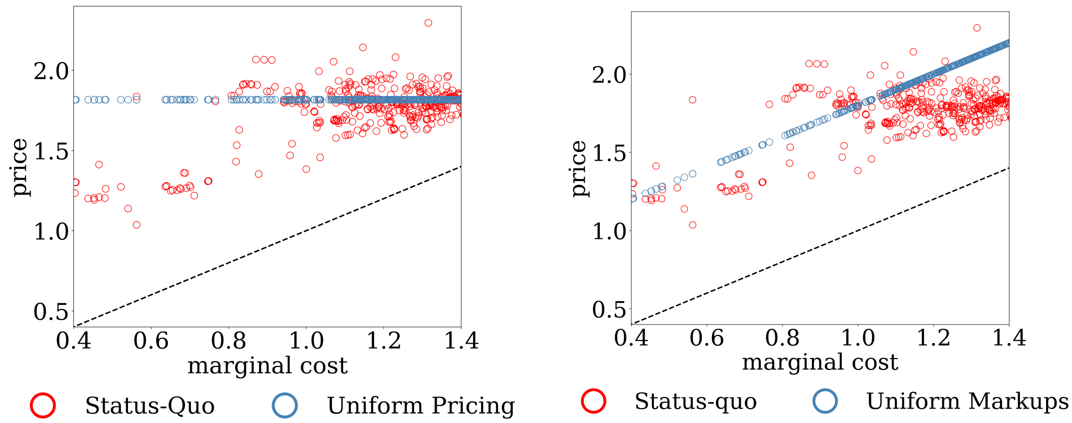
Note: Note: This table displays changes in consumer surplus, profits, and total surplus by comparing three different scenarios against the actual case (nationalization under discretion) during Jun-2012 to Dec-2012. *Full CS* column outlines the effects of a scenario where YPF fully internalizes consumer and producer surplus

Table C.16. Effects on welfare: price rules vs status-quo

	Actual	Uniform Pricing	Uniform Mark-ups	Full CS
Panel 1: Oil-Producing				
CS	25.1	21.7	25.7	40.0
High Income	23.1	19.8	23.7	32.5
Middle Income	1.4	1.0	1.2	5.7
Low Income	0.7	1.0	0.8	1.8
Panel 2: Other Provinces				
CS	98.8	97.2	94.3	138.5
High Income	86.2	84.3	84.0	101.8
Middle Income	10.1	9.8	8.0	30.2
Low Income	2.4	3.1	2.3	6.5
Panel 3: All Provinces				
CS	123.9	118.9	120.0	178.5
High Income	109.3	104.1	107.6	134.3
Middle Income	11.5	10.8	9.2	35.9
Low Income	3.1	4.1	3.2	8.4

Note: Note: This table presents changes in consumer surplus, by income group and province type, when comparing three different scenarios against the actual case (nationalization under discretion) for the period Jun-2012 to Dec-2012. *Full CS* column outlines the effects of a scenario where YPF fully internalizes consumer and producer surplus

Table C.17. Effects on consumer surplus: price rules vs status-quo



Note: Note: Figures (a) and (b) present prices and under different scenarios.

Figure C.28. Prices vs marginal costs: status-quo vs counterfactuals

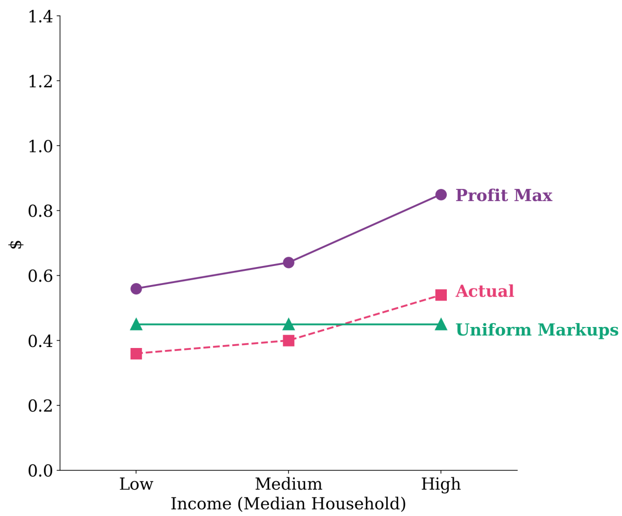


Figure C.29. Correlation between markups and income under different scenarios

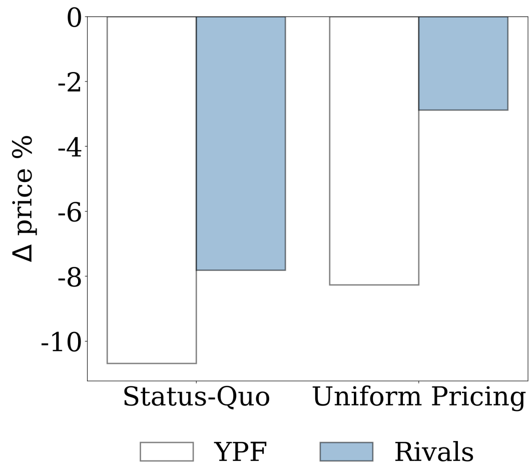


Figure C.30. Price responses under different scenarios