

Consumer Inertia and Market Power*

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Abstract

We study the pricing decision of firms in the presence of consumer inertia. Inertia can arise from habit formation, brand loyalty, switching costs, or search, and it has important implications for the interpretation of equilibrium outcomes and counterfactual analysis. In particular, consumer inertia affects the scope of market power. We show that the effects of competition on prices and profits are non-monotonic in the degree of inertia. Further, a model that omits consumer inertia tends to overstate the marginal effect of competition on price, relative to a benchmark that accounts for consumer dynamics. We develop an empirical model to estimate consumer inertia using aggregate, market-level data. We apply the model to a hypothetical merger of two major retail gasoline companies, and find that a static model predicts price increases greater than the price increases predicted when accounting for dynamics.

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1 Introduction

Consumers are often more likely to buy a product if they have purchased it previously. This tendency reflects both exogenous preferences and state-dependent utility that is affected by past behavior (Heckman, 1981). Consumer state dependence, or inertia, may arise from habit formation, brand loyalty, switching costs, or search. There is a rich empirical literature that establishes the presence of such inertia in a variety of markets.¹ This behavior is typically identified by examining the choice patterns of individual consumers over time.

In this paper, we develop an empirical model consumer inertia that can be estimated using aggregate market-level data. Our specific model captures a product-specific “affiliation” for the most recently purchased product and nests typical implementations of dynamic consumer behavior. To disentangle heterogeneity in preferences from state dependence arising from previous purchases, we impose a demand system and rely on the panel structure of our data. Intuitively, after adjusting for cross-sectional fixed effects, consumer inertia is captured by the residual correlation in shares over time (and their relation to prices). We consider the implications of this model on the pricing behavior of firms, and, in particular, on the potential for market power.

In response to consumer affiliation, profit-maximizing firms will internalize the effect of their current price on the distribution of affiliated consumers in future periods. Over a long horizon, this will often lead firms to invest in future consumers by maintaining lower prices than the short-run optimum. However, these prices are typically higher than in a counterfactual world in which consumers do not exhibit state dependence in purchasing behavior. We define the extent to which prices are higher due to consumer affiliation as *dynamic market power* over consumers. Dynamic market power tends to increase with the rate consumers become affiliated. We contrast this with *horizontal market power*, which is the ability of firms to raise price in response to a reduction in the number of independent competitors. The maximum potential for horizontal market power in a market is determined by the monopoly price. A key finding of our analysis is that horizontal market power is, on average, non-monotonic as consumer inertia increases. Horizontal market power increases at low rates of affiliation and decreases at high rates of affiliation.

Given these effects, it is natural to wonder whether (static) demand models that are typically employed in empirical work provide accurate counterfactual approximations to a world with consumer state dependence. We explore this question in the context of horizontal mergers, which allows us to examine the effect of competition on prices. Antitrust authorities will challenge a merger if the merging firms are expected to increase the price by a significant amount. The ability to accurately predict the price effect of a merger hinges on an appropriate representation of the firms’ pricing incentives. In the presence of consumer affiliation, a first-order

¹See the related literature section for examples.

determinant of price is its effect on future demand. A static model, which omits this incentive, will incorrectly attribute this effect to consumer elasticities and the degree of competition. As we demonstrate, static models consistently over-predict the price effects of a merger, compared to an analysis that accounts for the dynamic incentive to invest in future demand. Thus, failing to account for consumer inertia may overstate the potential for horizontal market power and affect merger enforcement.

Antitrust authorities often analyze mergers in markets that are likely to be characterized by consumer affiliation. For example, in its lawsuit against Swedish Match-National Tobacco, the Federal Trade Commission (FTC) cited strong brand loyalty as a barrier to entry.² Similarly, the US Department of Justice cited customer switching as an important factor in its case against the UPM-MACtac merger.³ In defense of its acquisition of TaxACT, H&R Block cited the importance of dynamic incentives in exerting downward pricing pressure post-merger (Remer and Warren-Boulton, 2014). Both the FTC and DOJ routinely investigate mergers in consumer products markets, where inertia in brand choice has been frequently documented.⁴ Yet, perhaps due to computational complexity and compressed investigative timelines, dynamics are seldom directly modeled when analyzing unilateral competitive effects. We develop a model that significantly reduces the computational and data burden of estimating the impact of these dynamics.

We apply the model using data from retail gasoline markets, where pricing patterns consistent with consumer affiliation have been documented (Borenstein (1991), Hastings (2004), Doyle et al. (2010)). Furthermore, retail gasoline has a direct link to current antitrust concerns. In June and December of 2017, the FTC challenged Alimentation Couche-Tard's acquisitions of Empire Petroleum Partners⁵ and Holiday,⁶ respectively, on the basis of overlapping retail gasoline stations in a number of states. The FTC argued that the merger with Holiday would reduce the number of independent competitors from four to three in five markets and from three to two in five other markets. Similar arguments were made for the merger with Empire Petroleum, which lead to the divestiture of 71 retail gas stations. The 4-to-3 and 3-to-2 heuristics are commonly cited by the antitrust authorities, and they are primarily informed by the logic of static models.

The demand model we introduce is a straightforward extension of the standard discrete-choice logit model with myopic consumers. In contrast to the typical random-coefficients model, we allow the distribution of unobserved heterogeneity to be state-dependent, affected

²See, "Commentary on the Horizontal Merger Guidelines," 2006, <https://www.justice.gov/atr/file/801216/download>

³Ibid.

⁴For example, Dubé et al. (2010) estimate state dependence in consumers' choices of orange juice and margarine, where the root cause is brand loyalty developed through consumption.

⁵<https://www.ftc.gov/news-events/press-releases/2017/06/ftc-requires-retail-fuel-station-convenience-store-operator>

⁶<https://www.antitrustalert.com/2017/12/articles/ftc-developments/the-latest-ftc-challenges-retail-fuel-station-and-convenience-store-transaction-requires-ten-localized-divestitures-in-wisconsin-and-minnesota/>

by past purchase behavior. We restrict the random coefficients to affect a single product for each consumer type, corresponding to our notion of product-level affiliation. A key contribution of the paper is that the model can be estimated using aggregate market-level shares and prices, which is the typical data used in demand estimation and merger simulation. Importantly, the model can also be estimated independently of supply-side assumptions, and we can therefore use the estimated demand model to test for forward-looking behavior by firms.

To provide intuition about the model, we first develop theoretical results for the optimal monopoly price. In the steady state, we show that optimal prices may either be higher or lower in the dynamic model compared to a static model, depending on the relative price sensitivity of affiliated and unaffiliated consumers. Thus, either the “invest” or “harvest” incentive may dominate, although both incentives matter in the steady state.

We then consider price competition in an oligopoly setting using numerical simulations. We demonstrate that affiliation can have a large effect on steady-state prices. In equilibrium, affiliation can raise oligopoly prices higher than the monopoly price with no affiliation. Second, we show that the percentage price effect of a merger may decrease with the rate of affiliation, implying that the usual intuition about effects of a merger may be misleading. When consumers are sufficiently price insensitive, then affiliation allows firms to capture a large portion of the monopoly rents pre-merger, resulting in a smaller increase in post-merger prices.

Next, we consider the empirical implications of failing to account for dynamic demand in a merger analysis. In this exercise, we calibrate a static demand model to data generated by the dynamic model and perform a merger simulation. Compared to the true impact of the merger, the (misspecified) static model systematically over-predicts merger price effects. In the dynamic model, the incentive to invest in future demand pushes prices down, and this effect remains after the merger. Due to the suppressed margins pre-merger, the static model falsely considers the products less differentiated; when competition is reduced post-merger, the static model then generates higher prices.

The dynamic model can be taken to data, which we demonstrate through an analysis of retail gasoline markets. We advance the empirical literature by developing an estimation method that accommodates dynamic demand but does not require the assumptions used in standard dynamic estimation techniques, such as those developed by Bajari et al. (2007) and Pakes et al. (2007), to identify the dynamic parameters. Importantly, we do not require supply-side assumptions about the competitive game or the expectations of firms to estimate demand. As supply-side behavior depends crucially on whether future shocks are expected or unexpected, we view this as a significant advantage.

The data needed to estimate the model are commonly used in the demand estimation literature, namely: prices, shares, and an instrument for prices. Nonetheless, we show that with firm-level shares (aggregated across all consumer types), it is possible to separately identify each firm’s current shares of affiliated and unaffiliated consumers, as well as the probability

that a consumer becomes affiliated after purchasing. Thus, we allow for endogenous unobserved heterogeneity through the presence of a serially correlated state variable for each firm. This flexibility has traditionally been a challenge for the estimation of dynamic models.

We estimate the model using a rich panel data set of prices, shares, and costs for retail gasoline stations. In this context, the model is best interpreted as one of habit formation, wherein some consumers return to the gas station from which they previously purchased without considering alternative sellers. We find evidence of strong demand dynamics. We estimate that 60 percent of consumers become affiliated to the brand from which they previously purchased on a week-to-week basis, and therefore effectively do not consider competitors.⁷ Affiliated consumers display a much lower price sensitivity. Unaffiliated consumers have an average elasticity of -7.7, whereas affiliated consumers have a near-zero average elasticity. Though unaffiliated consumers are a minority of all consumers that purchase gasoline, they are important for disciplining prices in equilibrium. Across all consumer types, firms face an average elasticity of -3.1.

To highlight the importance of accounting for dynamics when predicting firm behavior, we impose a supply-side model of price competition. In contrast to the literature, we invoke relatively weak assumptions about supply-side behavior in order to conduct counterfactual analysis. From the estimated demand model, we obtain the derivative of static profits, which we use to infer the dynamic component of the firms' first-order conditions. We project these estimates onto state variables to construct a reduced-form approximation to the dynamic pricing incentives. This approximation is consistent with a model of Markov perfect equilibrium where firms use limited state variables to forecast their continuation value. Using this approximation, we perform a merger analysis between two major gasoline retailers and re-compute the price-setting equilibrium in each period. With the dynamic model, we estimate that prices would increase by 3.3 percent post-merger. A static model, on the other hand, predicts an average price increase of 5.9 percent, which would likely result in greater antitrust scrutiny. Therefore, the dynamic incentive to invest in future demand mitigates the increase in horizontal market power that arises from a merger.

Prior to estimating the model, we present reduced-form evidence of dynamic demand and dynamic pricing in retail gasoline markets.⁸ Consistent with investment in affiliated consumers, we find that new entrants initially price lower than established firms but raise prices over time. We then examine cost pass-through. Using the data to separate out expected and unexpected costs, we show that firms respond differentially to these two measures. Importantly, firms begin raising prices in anticipation of higher costs approximately 28 days prior to an expected cost

⁷Interestingly, the National Association of Convenience Stores, a retail fueling lobbying association, found in its 2018 annual survey that 57 percent of respondents have a preference for a specific brand to fill up gasoline. See, <https://www.convenience.org/Topics/Fuels/Documents/How-Consumers-React-to-Gas-Prices.pdf>

⁸By dynamic pricing we mean that there are intertemporal spillovers. This should not be confused with static pricing in response to changing market conditions, which is often colloquially referred to as "dynamic pricing."

shock.

Related Literature

We consider the implications of consumer state dependence on the pricing behavior of firms, building on an empirical literature that includes Dubé et al. (2009). We contribute to the literature by examining the effect of competition on price in such settings. State dependence can have a large effect on the interpretation of outcomes when studying inter-firm competition. Our analysis of mergers complements theoretical work on dynamic price competition when consumers are habit-forming or have switching costs. Such features link directly to our notion of consumer affiliation. For examples, see Farrell and Shapiro (1988), Beggs and Klemperer (1992), and Bergemann and Välimäki (2006).⁹ Our empirical model can be used to assess the impacts of competition using real-world data.

We contribute to the empirical literature that estimates state dependence in consumer preferences. Meaningful switching costs, due to brand loyalty or consumer inertia, have been found in consumer packaged goods (Shum, 2004; Dubé et al., 2010), health insurance (Handel, 2013), and auto insurance (Honka, 2014). Conceptually, our model shares similar features to that of Dubé et al. (2009, 2010). However, the existing literature has relied on consumer-specific purchase histories to document state dependence, whereas our method allows for the recovery of such state dependence using aggregate market-level data. This is a central contribution of the paper. For an analysis of inter-firm competition, market-level data tends to be more readily available; this highlights the utility of our empirical approach.

We contribute to a growing body of empirical models of dynamic demand. Existing work focuses on different contexts that drive dynamic behavior. Hendel and Nevo (2013) consider a model with storable goods and consumer stockpiling. Gowrisankaran and Rysman (2012) and Lee (2013) consider the purchase of durable goods with forward-looking behavior by consumers. In contrast to these papers, we focus on settings with positive dependence in purchasing behavior over time. The literature highlights the issue, common to our setting, that misspecified static models will produce biased elasticities. Hendel and Nevo (2013) point out that this will matter in a merger analysis. We complement this point by providing a case in which the dynamic incentives, rather than biased elasticities, are a primary concern in model misspecification.

We propose a reduced-form method to approximate the dynamic incentives in supply-side pricing behavior, which allows us to side-step some of the challenges present in the estimation of dynamic games. Compared to value-function approximation methods proposed by Bajari et al. (2007) and Pakes et al. (2007), we rely more heavily on the structure of the demand model and place weaker assumptions on supply-side behavior. Our focus on the pricing behavior of firms

⁹There are alternative strategic reasons for dynamic pricing, including experience goods (Bergemann and Välimäki, 1996), network effects (Cabral, 2011), learning-by-doing (Besanko et al., 2017), and search (Stahl, 1989).

precludes the use of several developments in the conditional choice probabilities literature, which relies on discrete actions (e.g., Aguirregabiria and Mira, 2007; Arcidiacono and Miller, 2011). For a helpful summary of some developments in the estimation of dynamic games, see Aguirregabiria and Nevo (2013).

Finally, we contribute to the literature on cost pass-through, in general, and in retail gasoline markets, specifically. Weyl and Fabinger (2013) demonstrates the valuable information embedded in firm marginal cost pass-through rates, such as tax incidence and the welfare consequences of third-degree price discrimination. Miller et al. (2016) shows that cost pass-through estimates can be used to predict the price effects from mergers. In this article, we find that estimates of cost pass-through that don't account for anticipatory price responses can yield biased estimates in markets where dynamic demand is present. We also contribute to the literature that estimates dynamic price adjustments in retail gasoline markets (Borenstein et al., 1997; Lewis, 2011). Borenstein and Shepard (1996) show that tacitly colluding firms will decrease price with expected future cost changes and find support for this behavior using retail gasoline data. In our habit-formation setting, we find that competing firms increase current prices in response to a future positive cost shock. These anticipatory price responses are consistent with equilibrium outcomes in non-collusive markets.

2 A Model of Oligopolistic Competition with Consumer Inertia

We develop a dynamic model of oligopolistic competition with product differentiation where consumers may become affiliated with the firm from which they purchased previously. Affiliation may be interpreted as habit formation, brand loyalty, switching costs, or search. Consumers in the model are myopic in that they maximize current period utility rather than a discounted flow of future utility. This assumption is likely a good fit for retail gasoline markets, where consumers do not choose a gas station anticipating that it will limit their future choice set; rather, some consumers are likely to return to the same gas station due to habit-formation or brand loyalty.

As detailed below, we introduce consumer dynamics by allowing for endogenous unobserved heterogeneity in a differentiated product demand model. We then place the demand model into a dynamic oligopoly setting. Even though consumers are myopic, key dynamics arise when firms internalize the effect of sales today on future profits through the accumulation of affiliated consumers.¹⁰ We use the model to numerically examine the impact of consumer inertia on market power, in general, and in the context of horizontal mergers.

¹⁰Slade (1998) estimates a model of habit-forming consumers and sticky prices. That model, however, explicitly imposes a cost of price-adjustment. Our model does not rely upon a menu cost to explain dynamic price adjustments.

2.1 Demand

We extend the standard logit discrete choice model to allow for unobserved heterogeneity that depends on past purchases. The first assumption below presents a random coefficients utility formulation with myopic choice. The second assumption restricts the random coefficients so that the type-specific utility shock affects only a single product, corresponding to our notation of consumer affiliation. The third assumption places restrictions on the evolution of consumer types over time.

Assumption 1: Myopic Discrete Choice Consumers in each market select a single product $j \in J$ that maximizes utility in the current period, or they choose the outside good (indexed by 0). For the empirical model, we make the additional assumption that utility follows the random-coefficient logit setup. Consumers are indexed by discrete types $i \in I$, and we allow for the distribution of types to change endogenously over time.

A consumer n of type i receives the following utility for choosing product j :

$$u_{jt}^{(n)}(i) = \delta_{jt} + \sigma_{jt}(i) + \epsilon_{jt}^{(n)}. \quad (1)$$

Consumers receive an additively-separable common component δ_{jt} , a type-specific shock $\sigma_{jt}(i)$, and an idiosyncratic shock, $\epsilon_{ijt}^{(n)}$. The common component will typically be a function of firm j 's price, and takes the form $\delta_{jt} = \xi_j + \alpha p_{jt}$ in the standard logit model (with $\alpha < 0$). The type-specific shock, $\sigma_{jt}(i)$, may be also be a function of firm j 's price, if consumers are less sensitive to the price of the product to which they are affiliated, as is the case in our empirical application.

We denote the probability that a consumer of type i chooses product j as $s_{jt}(i)$. We normalize the utility of the outside good to be zero. Additionally, we define the type 0 consumer to be “unaffiliated,” and we assume that this type has no state-dependent preference, i.e., $\sigma_{jt}(0) = 0 \forall j$. Given the standard assumption of a type 1 extreme value distribution on the utility shock, $\epsilon_{jt}^{(n)}$, the choice probabilities of consumers conditional on type are:

$$s_{jt}(0) = \frac{\exp(\delta_{jt})}{1 + \sum_k \exp(\delta_{kt})} \quad (2)$$

$$s_{jt}(i) = \frac{\exp(\delta_{jt} + \sigma_{jt}(i))}{1 + \sum_{k/i} \exp(\delta_{kt} + \sigma_{jt}(i))}. \quad (3)$$

The observed share for firm j is given by the weighted average of choice probabilities by types: $S_{jt} = \sum_{i=0}^I r_{it} s_{jt}(i)$, where r_{it} is the fraction of consumers of type i .

The mean utility δ_{jt} may depend on time varying-observable characteristics as well as fixed effects. In the empirical application, we makes use of this latter feature to allow for serial

correlation in unobservable utility shocks over time.

Assumption 2: Single-Product Affiliation We now place restrictions on the type-specific demand shocks, $\sigma_{jt}(i)$. We assume that each consumer type has an affiliation (utility shock) to a single product. Further, we assume that there is a single type corresponding to each product. Thus, a consumer of type j is affiliated to product j . The type-specific demand shocks for other products are zero, i.e. $\sigma_{jt}(i) = 0 \forall i \neq j$.

Thus, we define *affiliation* to be a product-specific state dependence in preferences. We say that a consumer of type j is affiliated with product j , as this consumer has a perceived benefit of $\sigma_{jt}(j)$ relative to unaffiliated (type 0) consumers. The affiliation shock $\sigma_{jt}(j)$ has different interpretations depending on the underlying mechanism:

- **Brand loyalty** The model has a direct interpretation of brand loyalty when $\sigma_{jt}(j)$ is a positive level shock that reflects an internal benefit for purchasing from the same brand.
- **Switching costs** The model may be interpreted as a switching cost model when $\sigma_{jt}(j)$ is a level shock representing the costs (physical and psychic) of switching to another brand, $i \neq j$. This interpretation is empirically indistinguishable from the brand loyalty model because only the relative utilities matter in the logit formulation of the discrete choice model.
- **Habit formation** In the habit formation interpretation, a consumer gets either an extra benefit for repeating earlier behavior or bears a cost for adjusting behavior. $\sigma_{jt}(j)$ represents the net benefit. In contrast to the switching cost model, other aspects of preferences may change. For example, consumers may become less price sensitive to the affiliated product, in addition to realizing a level shock.
- **Search** In the special case where $\sigma_{jt}(j)$ renders affiliated consumers inelastic, the model has a search interpretation. In this case, the unaffiliated consumers are those that engage in search and realize full information about the choice set. Affiliated consumers are “non-searchers” who simply buy the previous product. This extends a standard search model (e.g., Varian, 1980; Stahl, 1989) by (i) having non-searchers default to the previous product, rather than randomizing, and (ii) endogenizing the distribution of searchers and non-searchers.

Distinguishing among these different mechanisms lies outside of the scope of this paper but may be important, especially when examining questions about welfare. The brand loyalty model and the switching cost model can have identical outcomes but divergent welfare predictions, as $\sigma_{jt}(j)$ is a net benefit in the former and a net cost in the latter.

Assumption 3: Evolution of Consumer Types Types are not fixed for a consumer, but they may depend dynamically on previous behavior. We assume that the evolution of types follows a Markov process, where the state can be expressed as a function of the joint distribution of types and choices in the previous period.

Given the previous assumption that there is a one-to-one mapping between types and an affiliation for each product, we implicitly assume that consumers are symmetric within a market. Thus, we can express the distribution of consumer types in any period as a function of the distribution of choices in the previous period. For example, the share of consumer type j , r_{jt} , might be expressed as $r_{jt} = f(S_{j(t-1)})$, where $S_{j(t-1)}$ is the aggregate share of consumers (across all types) that chose product j in the previous period.

We make the assumption that consumers that purchase product j become affiliated with product j in the next period at a given rate: $r_{jt} = \lambda_{jt}S_{j(t-1)}$. Under the habit-formation interpretation, a (random) fraction λ_{jt} of consumers that purchased j in the previous period are habituated to product j . We allow this fraction to vary with observable characteristics of the firm and market. The remaining $(1 - \lambda_{jt})S_{j(t-1)}$ consumers transition to type 0, along with any consumers that chose the outside good.

2.2 Supply

We assume that firms set prices to maximize the net present value of profits. In contrast to the typical setup for a dynamic game, we make relatively weak assumptions about the perceived continuation value, which depends on expectations and discount rates. We restrict attention to Markov perfect equilibria.

First, we define firm j 's aggregate share as:

$$S_{jt} = (1 - \sum_{i \neq 0} r_{it})s_{jt}(0) + \sum_{i \neq 0} r_{it}s_{jt}(i). \quad (4)$$

Thus, a firm's total share of sales can be written as a weighted sum of its share of unaffiliated consumers, $s_{jt}(0)$, and affiliated consumers, $s_{jt}(i)$. Note that firm j will make sales to consumers affiliated to other firms $j \neq i$, but the probability that such consumers will choose firm j is strictly lower than the choice probability of an unaffiliated consumer when the utility shocks $\{\sigma_{jt}(i)\}$ are positive.

Assumption 4: Competition in Prices We assume that firms set prices in each period to maximize the net present value of profits from an infinite-period game. Prices are set as a best response conditional on the state and contemporaneous prices of rival products. Firms cannot commit to future prices. The state vector in each period is summarized by marginal costs, c_t , the distribution of consumer types, r_t , and other variables that are captured by the vector, x_t ,

such as expectations about future costs. Entry is exogenous.¹¹ The firm's objective function can be summarized by the Bellman equation:

$$V_j(c_t, r_t, x_t) = \max_{p_{jt}|p_{kt}, k \neq j} \{(p_{jt} - c_{jt})S_{jt} + \beta E(V_j(c_{t+1}, r_{t+1}, x_{t+1})|p_t, c_t, r_t, x_t)\}. \quad (5)$$

Prices in each period optimize the sum of the continuation value and current-period profits, $(p_{jt} - c_{jt})S_{jt}$. Both of these components depend upon marginal costs and the distribution of consumer types, r_t . Thus, firms anticipate both future marginal costs and how price affects the future distribution of consumer types. Note that the state space does not include previous period prices. We therefore exclude strategies that depend directly upon competitors' historical prices, such as many forms of collusion.

Assumption 5: Expectations We place minimal restrictions on the expectations and discount factors for each firm. Consistent with the Markov perfect framework, we make the relatively weak assumption that the continuation value function is stable conditional on the state and prices.

Thus, market equilibrium is characterized by consumers making (myopic) utility-maximizing purchase decisions and firms pricing as the best response to other firm's prices, conditional on the state.

2.3 Theoretical and Numerical Analysis

To develop an understanding of pricing incentives in markets with consumer inertia, we consider a deterministic setting where marginal costs are constant. We now introduce competition into the model and use numerical methods to analyze steady-state prices in an oligopoly game¹² with Bertrand price-setting behavior. For the numerical exercise, we specify the utility of a consumer as follows:

$$u_{kt}^{(n)}(i) = \xi_k + \alpha p_{kt} + \mathbb{1}[i = k](\bar{\xi} + \bar{\alpha} p_{kt}) + \epsilon_{kt}^{(n)}. \quad (6)$$

Here, $\mathbb{1}[i = k]$ takes a value of one if a consumer of type i purchases from firm $k = i$, and zero otherwise. For unaffiliated consumers, the indicator function equals zero for all k . Assuming the error term, $\epsilon_{kt}^{(n)}$, follows the type-1 extreme value distribution, we get the market share specified in equation (2) in the previous section, which reduces to the standard logit model if $\bar{\xi} = \bar{\alpha} = 0$.

Each firm i sells a set of products, $j \in J_i$, and maximizes the expected discounted value of profits. Therefore, firm i 's value function takes the following form:

¹¹Entry and exit are infrequent in retail gasoline.

¹²We provide a theoretical analysis of the monopolist's problem in the Appendix.

$$V_i(r) = \max_{p_i | p_{-i}} \pi_i(p, r) + \beta V_i(r'). \quad (7)$$

Here, p and r are vectors of prices and affiliated customers, respectively, and $r' = f(p, r) = \lambda \cdot s(p, r)$ is a vector specifying each firm's affiliated customers in the next period. Static profits are $\pi_i(p, r) = \sum_{j \in J_i} (p_j - c_j) \cdot s_j(p, r)$. We drop the expectations operator, as the only source of uncertainty in the model is the realizations of marginal costs, which are fixed in the steady-state. To find the steady-state prices and affiliated shares for each firm, we focus on Markov perfect equilibrium.¹³ Firm i 's profit-maximizing first-order condition is then:

$$\sum_{l \in J_i} \frac{\partial \pi_l}{\partial p_j} + \beta \frac{dV_i(r')}{dr'} \frac{dr'}{dp_j} \quad \forall j \in J_i = 0. \quad (8)$$

Next, we specify the derivatives of equation (7) with respect to r and evaluate them at the prices that solve each firm's first-order condition, which will be the prevailing prices at the steady-state. These derivatives, in conjunction with the steady-state condition, $\frac{dV'}{dr'} = \frac{dV}{dr}$, yield the following system of equations:

$$\underbrace{\frac{dV_i(r)}{dr}}_{J \times 1} = \underbrace{\left[\frac{\partial \pi_i}{\partial p} \frac{dp}{dr} + \frac{\partial \pi_i}{\partial r} \right]}_{J \times 1} \underbrace{\left[I - \beta f_p(p, r) \frac{dp}{dr} - \beta f_r(p, r) \right]}_{J \times J}^{-1}. \quad (9)$$

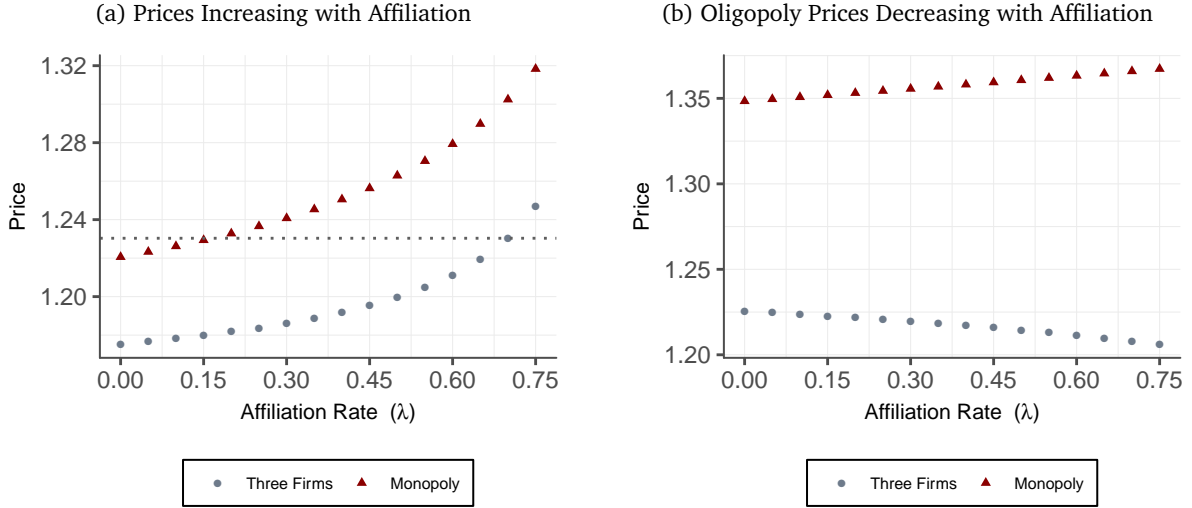
In this equation, $\frac{\partial \pi_i}{\partial p}$, $\frac{\partial \pi_i}{\partial r}$, $f_p(p, r)$, $f_r(p, r)$ are known, conditional on values of p and r . The remaining unknowns are $\frac{dp}{dr}$ and $\frac{dV_i(r)}{dr}$. To solve the model, we impose the steady-state condition governing the evolution of affiliated customers, $r' = r$. The full set of steady state conditions, provided by equation (9) and $r' = r$, allow us to solve for steady-state prices and shares, conditional on the $J \times J$ derivative matrix, $\frac{dp}{dr}$. The values of $\frac{dp}{dr}$ are determined by the model. In our simulations, we solve for these values numerically using a local approximation method. For additional details, see the Appendix.

For the oligopoly analysis, we simulate symmetric three-firm markets. In this setting, symmetry is imposed by restricting the utility parameters, ξ_i , $\bar{\xi}$, and $\bar{\alpha}$, and marginal cost to be the same across all firms. To illustrate the impact of affiliation on pricing incentives, we plot the equilibrium prices for two different sets of utility parameters in Figure 1.

Panel (a) of Figure 1 plots the equilibrium prices for a monopolist and a three-firm symmetric market, for increasingly large values of λ and otherwise identical demand parameters. The equilibrium prices increase with the rate of affiliation. This figure highlights the potential importance of affiliation. In the three-firm market, when consumers have high rates of affiliation ($\lambda \geq 0.70$), the equilibrium prices are higher than the monopoly price for static demand ($\lambda = 0$). Thus, intuition about the ability of competition to discipline prices should be paired

¹³Although we do not prove that the equilibrium is unique, the simulation results support there being a single steady-state equilibrium.

Figure 1: Monopoly and Oligopoly Prices with Consumer Affiliation



Notes: Panel (a) is generated using the following parameter values: $\xi = 6$, $\bar{\xi} = 5$, $\alpha = -6.5$, and $\bar{\alpha} = 5.85$. Panel (b) is generated using $\xi = 6.6$, $\bar{\xi} = 0.9$, $\alpha = -5.7$, and $\bar{\alpha} = 0.6$. Marginal cost is set to one for both figures.

with an understanding of consumer dynamics, as affiliation can offset or even overwhelm the horizontal effects of competition.

Panel (b) shows that the interaction of competition and affiliation can have surprising qualitative results. For a different baseline set of demand parameters from those of panel (a), the oligopoly price is decreasing in the rate of affiliation, even though the monopoly price is increasing. Dynamic market power, defined by the price increase relative to the price with no inertia, may be negative. Thus, the relationship between equilibrium prices and dynamics may depend upon market structure.

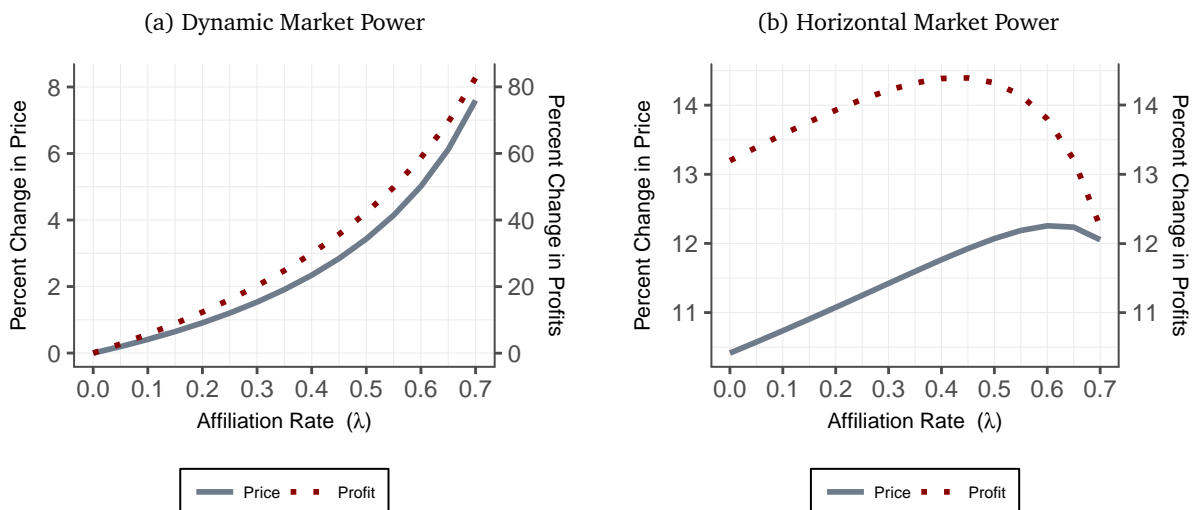
2.3.1 The Scope of Market Power

To summarize relationship between consumer inertia and market power in our model, we use simulations to decompose the potential impacts of dynamic and horizontal market power. To measure dynamic market power, we compare the oligopoly price with consumer affiliation to a baseline price where consumers have no state dependence. To measure horizontal market power, we compare the monopoly price to the oligopoly price, conditional on the demand parameters.¹⁴

To provide a generalizable analysis, we attempt to simulate data from the support of parameters that produce reasonable outcomes for margins and shares. We employ a “shotgun”

¹⁴Note that we use a (competitive) oligopoly price as a baseline, rather than price equal to marginal cost. Also, as marginal cost is constant across simulations, using price as a measure of market power is equivalent to commonly used price-cost metric.

Figure 2: The Scope of Market Power



Notes: Panel (a) displays the mean percent price increase and mean percent profit increase for a three-firm oligopoly above the baseline model with no dynamics in consumption ($\lambda = 0$). Note that the profits are scaled by a factor of 10, which is labeled on the right axis. Panel (b) displays the marginal effects, in terms of mean percent price increase and mean percent profit increase, of a merger to monopoly for different values of λ . The plots reflect 275 baseline parameter values of $(\xi, \bar{\xi}, \alpha, \bar{\alpha})$ that converged for $0 \leq \lambda \leq 0.7$, or 4,125 markets in total.

approach, generating simulations with many different parameters and selecting only the markets that meet certain criteria. We first take Halton draws of the demand parameters such that $\xi \in [-3, 17]$, $\bar{\xi} \in [0, 20]$, $\alpha \in [-15, 0]$, $\bar{\alpha} \in [0, 15]$, $\alpha + \bar{\alpha} < 0$, and set each firm's marginal cost to one. For each draw of these demand parameters, we construct three-firm markets for $\lambda \in \{0.05, 0.10, \dots, 0.95\}$. Finally, we restrict the analysis to markets where firms have shares between 0.05 and 0.30 (yielding an outside share between 0.10 and 0.85) and margins between 0.10 and 0.75. The data generating process yields 8,025 markets whose parameters are summarized in Appendix Table 11. The range for each parameter is selected such that parameter values toward each edge of the range result in outcomes that fall above or below our share and margin criteria.

In Figure 2, we plot the effects of affiliation and reduced competition on prices and profits. The plots employ simulation results from the 275 baseline parameter values of $(\xi, \bar{\xi}, \alpha, \bar{\alpha})$ that converged for $0 \leq \lambda \leq 0.7$, or 4,125 markets out of the 8,025 that meet the above qualifications. Panel (a) shows that, on average, prices and profits increase with the rate at which consumers become affiliated. This demonstrates that in the steady-state of the model, the “harvesting” incentive tends to dominate the “investment” incentive. Perhaps surprisingly, the effect on profits is roughly ten times the effect on prices (note the right axis). This highlights the importance of the investment incentive that firms face in this setting. As the affiliation rate increases, there is a modest increase in price but a large increase in the share of affiliated customers in the fol-

lowing period, generating correspondingly large increases in profits. In total, dynamic market power tends to increase with consumer inertia, but it is dampened by the incentive to invest in future demand.

In panel (b), we plot the effect on prices and profits that a monopolist realizes, relative to the “competitive” oligopoly, as the rate of consumer affiliation increases. These effects represent the scope for horizontal market power, either explicitly via merger or potentially through collusion. The gain in profits from moving to the monopoly outcome is non-monotonic on average and decreases with λ for $\lambda > 0.45$. Correspondingly, we also find that the price increases are non-monotonic. The non-monotonicity is due to dynamic market power decreasing the potential for horizontal market power as consumer inertia becomes more prevalent. As the rate of affiliation increases, consumers are less likely to view oligopoly firms as substitutes. If the strength of affiliation is sufficiently strong then firms can extract the majority of the consumer surplus from their own customers, which limits the scope of horizontal market power.

2.3.2 Consumer Inertia and Mergers

To further demonstrate the effect of consumer inertia on price competition, we examine the impact on prices of a horizontal merger. We proceed by simulating symmetric three-firm markets as a baseline and allowing two of the firms to merge. The merged firm maintains both pre-existing firms as separate entities but maximizes their joint profits. Thus, we examine how dynamic incentives affect steady-state prices and the unilateral price effects arising from a merger. We also analyze the bias that arises when a static model is calibrated to data generated by the dynamic affiliation model and used for merger simulation. We find that ignoring the presence of consumer affiliation tends to overestimate the price effects of a merger.

For each parameterized market, we solve for the steady-state prices. Then, we simulate a merger between firms 1 and 2, leaving firm 3 as the non-merging firm. Table 1 summarizes the pre-merger equilibrium and the unilateral price increases of merging and non-merging firms. The “average” market is one that, a priori, would typically raise moderate concern from the US antitrust agencies; HHI (1287) falls in the “unconcentrated” range, but the change in HHI (858) generally warrants a thorough investigation. The average pre-merger difference between price and cost is 0.36, and the mean market share is 0.19. Using these mean values to calculate the “Upward Pricing Pressure” index, $\frac{0.19}{1-0.19} \cdot (1.36 - 1) = .084$, yields a value in the midpoint of 0.05-0.10, which are the thresholds suggested to trigger an investigation.¹⁵ The average percentage merger price effect, 4.5 percent, is nearly at the 5 percent threshold often used as the “small but significant non-transitory increase in price” by antitrust agencies in merger analysis. The full range of markets span those that lead to no scrutiny to those that almost certainly would be challenged. Thus, the simulations generate a reasonable set of markets within which to explore

¹⁵See, for example, Farrell and Shapiro (2010) and Miller et al. (2017). This calculation assumes that diversion is proportional to market share, which is often assumed at the early stages of an antitrust investigation.

Table 1: Simulation Summary Statistics

	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	N
Pre-Merger Price	1.36	0.39	1.11	1.15	1.39	3.99	8025
Pre-Merger Margin	0.23	0.14	0.10	0.13	0.28	0.75	8025
Pre-Merger Market Share	0.19	0.08	0.05	0.12	0.26	0.30	8025
HHI: Pre-Merger	1287	849	75	460	2079	2699	8025
Δ HHI	858	566	50	307	1386	1800	8025
Merger Price Δ	4.54	3.73	0.34	2.11	5.64	25.15	8025
Non-Merging Price Δ	0.52	0.78	-0.19	0.03	0.73	6.55	8025
Prediction Bias	0.39	0.68	-2.47	0.04	0.48	7.73	8025
Prediction Bias (pctg.)	9.47	15.99	-18.52	1.38	12.33	330.73	8025
Dynamic Elasticity: Unaffiliated	-7.02	3.28	-17.26	-9.45	-4.32	-1.37	8025
Dynamic Elasticity: Affiliated	-3.60	2.78	-13.45	-5.27	-1.34	-0.00	8025
Dynamic Elasticity: Weighted	-5.37	2.62	-13.65	-7.31	-3.20	-0.77	8025
Static Elasticity	-5.67	2.42	-10.00	-7.72	-3.60	-1.33	8025

Notes: Margin is defined as $\frac{p-c}{p}$. Δ HHI is calculated at the pre-merger shares. Merger Price Δ is the percentage price increase from the merger. Prediction Bias is the static minus the dynamic prediction, in percentage points. Prediction Bias (pctg.) is the Prediction Bias divided by the dynamic Merger Price Δ . The weighted dynamic elasticity is the average of the unaffiliated and affiliated elasticities weighted by the fraction of the firm's customers of each type.

the pricing incentives of firms in the consumer affiliation model.

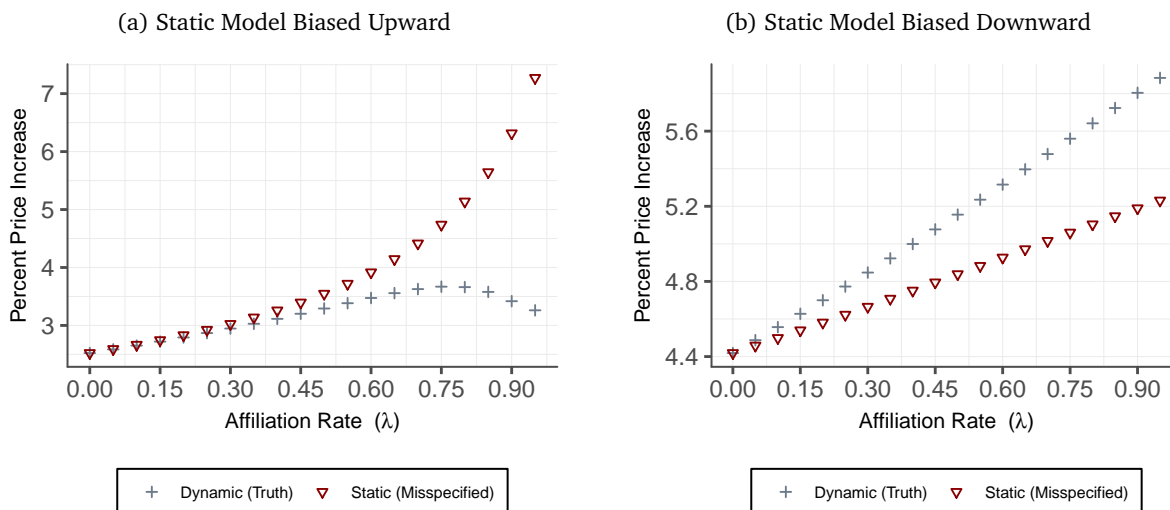
On average, increasing the rate of affiliation (λ) and the strength of the affiliation ($\bar{\alpha}$ and $\bar{\xi}$) tend to increase both pre-merger prices and the price effects arising from a merger. Table 12 in the Appendix provides results from regressions of these outcomes on the demand parameters. However, these relationships do not hold in every instance, and may interact in interesting ways. As show in Figure 1, prices may increase or decrease in the rate of affiliation. In a small number of markets, we find that the relationship between λ and prices is non-monotonic.

2.3.3 Model Misspecification in Merger Simulation

The above results suggest that affiliation has implications for counterfactual exercises, such as merger simulation. Failing to account for consumer inertia will result in biased elasticities from incorrect first-order conditions. Antitrust agencies often infer elasticities from markups calculated using accounting data (see Miller et al. (2013)), which omit the dynamic incentive of firms. In addition to generating incorrect elasticities, failing to account for the dynamic incentives in first-order conditions can have large direct effects on post-merger predictions.

To more precisely analyze the impact of model misspecification, we measure the implications of failing to account for consumer affiliation when calibrating demand and simulating a merger. To do so, we consider the following hypothetical scenario. The true underlying model is the three-firm market with consumer state dependence due to affiliation. A practitioner observes each firms' pre-merger prices, marginal costs, and aggregate market shares (rather than separately observing its unaffiliated and affiliated shares). This data is then used to recover

Figure 3: Simulated Merger Price Increases



Notes: Panel (a) is generated using the following parameter values: $\xi = 9.1$, $\bar{\xi} = 4.8$, $\alpha = -8.6$, and $\bar{\alpha} = 0.9$. Panel (b) is generated using $\xi = 6.6$, $\bar{\xi} = 0.9$, $\alpha = -5.7$, and $\bar{\alpha} = 0.6$. Marginal cost is set to one for both figures.

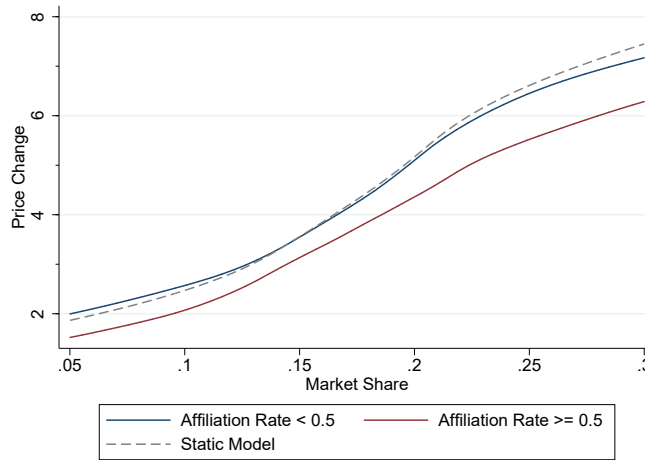
the demand parameters of the standard logit model, and then the price effects of a merger are simulated.¹⁶ We perform this experiment for each of the numerically generated markets.

Table 1 summarizes the prediction bias, defined as the static prediction minus the “true” affiliation price effect. The average prediction bias is 0.39 percentage points; dividing by the magnitude of the price change, this represents a 9.47 percent increase over the true price effect. While the average prediction bias is moderate, there is a fair amount of dispersion in the size of the bias; the 25th and 75th percentile of the bias, as a percentage of the price increase, is 1.38 percent and 12.3 percent, respectively. Usually, the static model over-predicts the true price change, but in 5.48 percent of simulations it predicts a smaller effect.

Figure 3 presents the results of the experiment for two individual markets. In panel (a), the “true” dynamic model and the misspecified static model generate similar price effects for affiliation rates (λ) less than 0.5. As λ increases above 0.5, however, the dynamic model generates lower price effects, as the post-merger investment effect increases relative to the pre-merger market structure. The static model, however, cannot account for this incentive, resulting in increasingly biased price predictions. By contrast, panel (b) demonstrates a parameterization where the static model consistently under-predicts the dynamic model. Moreover, for values of λ between 0.4 and 0.65, the true model yields price effects greater than 5 percent, while the biased prediction from the static model is below that threshold. As the US antitrust agencies may take 5 percent as the price threshold above which to take enforcement action, panels (a) and (b) demonstrate that not accounting for affiliation can lead to errors in enforcement action

¹⁶See Miller et al. (2016) for details on the calibration and simulation procedure for the logit model.

Figure 4: Price Increase by Market Share



Notes: The lines depict a local polynomial regression of firm 1's merger percent price change on its pre-merger market share. Markets where $\lambda < 0.5$ and $\lambda \geq 0.5$ are separately estimated. All markets are used for the static model.

in either direction.

On average, the static model tends to overstate the unilateral price effects of a merger. This is highlighted in Figure 4, which relates the merger price effect to the pre-merger market share of each symmetric firm. In line with intuition, the price effect of a merger is increasing with pre-merger market shares. To generate the graph, we run a local polynomial regression of the merger price effect on the firm's market share; we generate regression lines for (i) the affiliation model with $\lambda < 0.5$ (ii) the affiliation model with $\lambda \geq 0.5$ and (iii) the static model. The dynamic model and the static model yield similar predictions for low values of the affiliation rate. For higher affiliation rates, however, the static model over-predicts the dynamic model regardless of the pre-merger market shares. Thus, as the dynamic incentive to invest in future demand increases, the upward bias of the static model becomes greater in magnitude. The figure also highlights that for the dynamic model, conditional on observed market share, a greater affiliation rate suppresses merger price effects.

Interestingly, the static model is calibrated to be more elastic, on average, than the share-weighted elasticity in the dynamic model (-5.67 vs. -5.37). In the 60 percent of markets where the static model is calibrated to be more elastic, it still over-predicts the dynamic price effect. Thus, biased predictions from the static model arise primarily from the omission of dynamic incentives to invest in future demand, rather than a biased elasticity or mean utility parameters alone. In the static model, there is no incentive for the post-merger duopolist to invest in future demand, and therefore it sets its post-merger price simply to balance current marginal revenue and marginal cost. On the other hand, in the dynamic model, there is still a

Table 2: Simulation: Merger Price Change and Bias

	(1) Price Δ	(2) Price Δ	(3) Price Δ	(4) Bias	(5) Bias	(6) Bias
Pre-Merger Market Share	25.526*** (0.198)	25.487*** (0.194)	25.481*** (0.194)	3.392*** (0.087)	3.442*** (0.073)	3.450*** (0.072)
Pre-Merger Margin	20.596*** (0.113)	20.523*** (0.111)	20.512*** (0.111)	1.188*** (0.049)	1.279*** (0.041)	1.297*** (0.041)
λ		-1.126*** (0.065)	-1.148*** (0.065)		1.413*** (0.024)	1.446*** (0.024)
$ \frac{\bar{\alpha}}{\alpha} $			-0.087* (0.052)			0.118*** (0.019)
$\bar{\xi}$			-0.008*** (0.003)			0.013*** (0.001)
Constant	4.544*** (0.015)	4.544*** (0.015)	4.544*** (0.015)	0.392*** (0.007)	0.392*** (0.006)	0.392*** (0.006)
N	8025	8025	8025	8025	8025	8025

Notes: Observations are for firm 1. Price Δ and Bias are the merger price change and static prediction bias, respectively. All dependent variables are demeaned. Market share is the aggregate market share. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

post-merger incentive to invest in future demand, which imposes downward pressure on post-merger prices. In total, starting from the same pre-merger prices and margins, the static model leads to greater post-merger price effects, even when its demand parameters are biased toward greater elasticity.

Relatedly, another source of prediction bias is that the static model overstates the substitution between the merging firms' products, and greater substitutability generally leads to higher unilateral price effects.¹⁷ The logit model constrains substitution to be proportional to aggregate market shares. However, in the dynamic model, a fraction of each firm's customers are affiliated, and therefore less likely to switch to another product in response to a price increase than static predicts. Consequently, the logit model overstates substitution (and therefore competition) between the merging firms, which leads to an upwardly biased price prediction.

These results highlight the benefit of an empirical model that can account for consumer dynamics, which we pursue in the following section. However, for certain applications an informal analysis of consumer dynamics may provide a useful indication of static model bias. To provide directional guidance, we look at price changes as a function of pre-merger margins and shares, which are often used to simulate or approximate unilateral merger price increases (Miller et al., 2016). Columns (1)-(3) of Table 2 explore how the percentage price change from a merger relates to pre-merger margins and market shares, which are often directly observed, as well as

¹⁷The own-price elasticity captures both the substitutability between the merging products and the outside good. It is important to distinguish between these two for the appropriate intuition.

to primitives of the demand model. As is typically the case in static models, both pre-merger shares and margins are positively related to the size of the price change. Conditional on these observables, however, the dynamic parameters dampen the effect of the merger. The affiliation rate (λ), the relative affiliation price sensitivity effect, ($|\frac{\bar{\alpha}}{\alpha}|$), and the utility boost from affiliation ($\bar{\xi}$), all decrease the unilateral price impact for the merging firm.¹⁸ Correspondingly, the static model bias, which is the dependent variable in columns (4)-(6) of Table 2, increases with the dynamic parameters, conditional on the pre-merger shares and margins. Therefore, even if affiliation cannot be directly estimated, price change estimates should be revised downward if affiliation is expected to play an important role.

3 Reduced-Form Evidence of Dynamics

To motivate the empirical application, we provide evidence of dynamic demand and dynamically adjusting retail gasoline prices. A host of previous studies have found that retail gasoline prices may take multiple weeks to fully incorporate a change in marginal cost.¹⁹ One innovation of our study is that we use separate measures of unexpected and expected costs to see if, consistent with forward-looking behavior, firms respond differentially to these two types of costs.

3.1 Data

The analysis relies upon daily, regular fuel retail prices for nearly every gas station in the states of Kentucky and Virginia, which totals almost six thousand stations. As a measure of marginal cost, the data include the brand-specific, daily wholesale rack price charged to each retailer. We therefore almost perfectly observe each gas station's marginal cost changes, except for privately negotiated discounts per-gallon, which are likely fixed over the course of a year.²⁰ The data ranges from September 25th, 2013 through September 30th, 2015. The data was obtained directly from the Oil Price Information Service (OPIS), which routinely supplies data used in academic studies (e.g. Lewis and Noel 2011; Chandra and Tappata 2011; Remer 2015).

OPIS also supplied the market share data, which is used by industry participants to track shares. It is calculated from "actual purchases that fleet drivers charge to their Wright Express Universal card." The data is specified at the weekly, county/gasoline-brand level.²¹ Due to contractual limitations, OPIS only provided each brand's share of sales, not the actual volume.

¹⁸Results are directionally the same, but smaller in magnitude, for the non-merging firm. Results are presented in Appendix A.5. We also find that in 3.8 percent of simulations, the non-merging firm lowers its price in response to the merger. This is consistent with our empirical application, where we find that the non-merging firm tends lower its price in the counterfactual simulations.

¹⁹See Eckert (2013) for a comprehensive review of the literature.

²⁰The data also include all federal, state, and local taxes.

²¹In some instances, the brand of gasoline may differ from the brand of the station. For example, some 7-Eleven stations in the data are identified as selling Exxon branded gasoline.

Table 3: Regressions with Share as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)
Price	0.009*** (0.001)	0.000** (0.000)	0.004 (0.002)	-0.005 (0.004)	-0.073*** (0.017)
Lagged Share		0.973*** (0.001)	0.963*** (0.001)	0.554*** (0.002)	0.628*** (0.003)
Price Squared			-0.000 (0.000)	0.001 (0.001)	0.010*** (0.003)
Comp. Price (Mean)			-0.004*** (0.001)	-0.002 (0.001)	-0.108** (0.045)
Comp. Price (SD)			-0.000 (0.001)	0.003* (0.001)	0.086*** (0.024)
Comp. Stations			-0.000*** (0.000)	-0.000*** (0.000)	-0.004*** (0.000)
Num. Stations			0.000*** (0.000)	0.004*** (0.000)	0.000 (.)
Num. Brands			-0.001*** (0.000)	-0.003*** (0.000)	0.000 (.)
Week FEs				X	
County-Brand FEs				X	
Brand-State-Week FEs					X
Week-County FEs					X
County-Brand-WofY FEs					X
Observations	174421	169931	169788	169770	156078
R^2	0.00	0.95	0.95	0.96	0.98

Regression estimates indicate the correlation structure of shares over time. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Thus, to account for temporal changes in market-level demand, we supplement the share data with monthly, state-level consumption data from the Energy Information Administration (EIA).

3.2 Dynamic Demand: Correlation in Shares Over Time

Though ultimately the importance of demand-side dynamics in the data will be estimated by the model, it is informative to examine the reduced-form relationships between key elements. The dynamic model developed in the previous section is one in which today's quantity depends on the quantity sold last period. As motivation for this model, we present the results from reduced-form regressions of shares on lagged shares in Table 3.

This exercise demonstrates that even after including rich fixed effects to capture static variation in consumer preferences, lagged shares are a significant predictor of current shares. The residual correlation in shares over time in the most detailed specification captures deviations from specific county-brand seasonal patterns. A positive correlation is consistent with state dependence in consumption. In specification (2), we show that lagged shares explain 95 per-

cent of the variance in current shares, and the coefficient is close to one. In specification (3), we include measures of competition in the regressions, as well as a second-order polynomial in own price. The competition measures, which include the mean and standard deviations of competitor prices, are correlated with shares, but lagged shares still are the most important predictor of current shares. In specification (4), we include time and brand-county fixed effects. In the final specification (5), we include rich multi-level fixed effects: county-brand-(week of year), brand-state-week, and week-county. The coefficient of 0.628 on lagged shares in this specification indicates that deviations in shares are highly correlated over time, even when we condition on the most salient variables that would appear in a static analysis, adjust for brand-county specific seasonal patterns, and allow for flexible brand-state and county time trends. This finding is consistent with demand-side dynamics, as there are patterns in shares over time that are challenging to explain with contemporaneous variables.²²

3.3 Dynamic Pricing

We now present reduced-form evidence of dynamic pricing. Consistent with a model where firms accumulate affiliated consumers over time, we find that new entrants price lower relative to established competitors in the same market, and that this discount dissipates over time. Second, we examine cost pass-through and show that firms are slow to adjust to marginal cost changes. Moreover, firms anticipate expected changes in future costs by raising prices in advance of the change. In the presence of consumer affiliation a firm will change its current price in response to an expected future cost change, as it affects the current value of investing in future demand. The ability to separately estimate the response to expected and unexpected costs is a key innovation of our study.

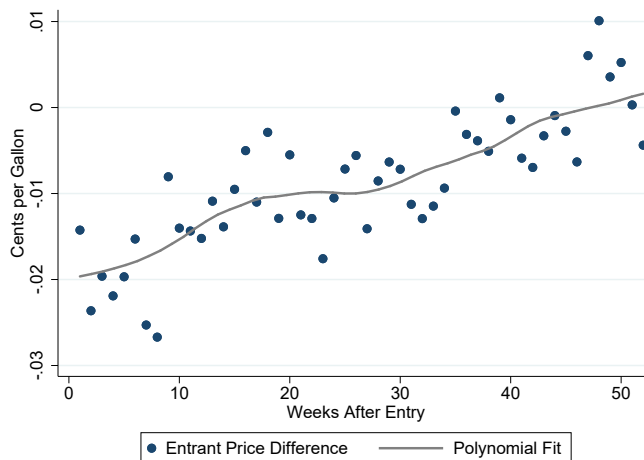
3.3.1 Dynamic Pricing of New Entrants

When forward-looking firms price to consumers that may become affiliated, there is an incentive to initially offer prices below the static optimum. In this setting, we expect a new entrant, all else equal, to initially price below its competitors. As the new entrant builds up its share of affiliated customers, its prices will gradually converge to its competition.

We test for and find evidence consistent with this dynamic pricing pattern in the data. To perform the analysis, we first identify a set of new entrants, defined as a gas station whose first price observation is at least six weeks after the start of the data and does not exit in the remainder of the sample. To ensure there is sufficient data and to control for composition effects in the analysis, we limit the set of entrants to those with at least one year of post-entry price data. Using this filter, we identify 193 entrants.

²²We have also estimated specifications that add lagged prices. Though the first lag is significant, there is almost no change to the lagged share coefficient.

Figure 5: New Entrant Prices



Notes: A data point measures the average difference between a new entrants price and the county average price, for the given number of weeks after entry. The line is created using local polynomial regression.

Figure 5 depicts the average difference between an entrant’s price and all other stations’ price in the same county, sorted by the number of weeks after entry. The figure demonstrates that gas stations enter with a price that is, on average, two cents per gallon less than incumbents’ prices. Entrants’ prices then slowly converge over time to the market average. A series of *t*-tests confirm the statistical significance of the results. For the first 8 weeks following entry, new entrants’ prices are significantly lower than the county average price.²³ This pattern is consistent with a profit-maximizing firm building up an affiliated customer base over time, and raising its price to a gradually less elastic set of consumers.

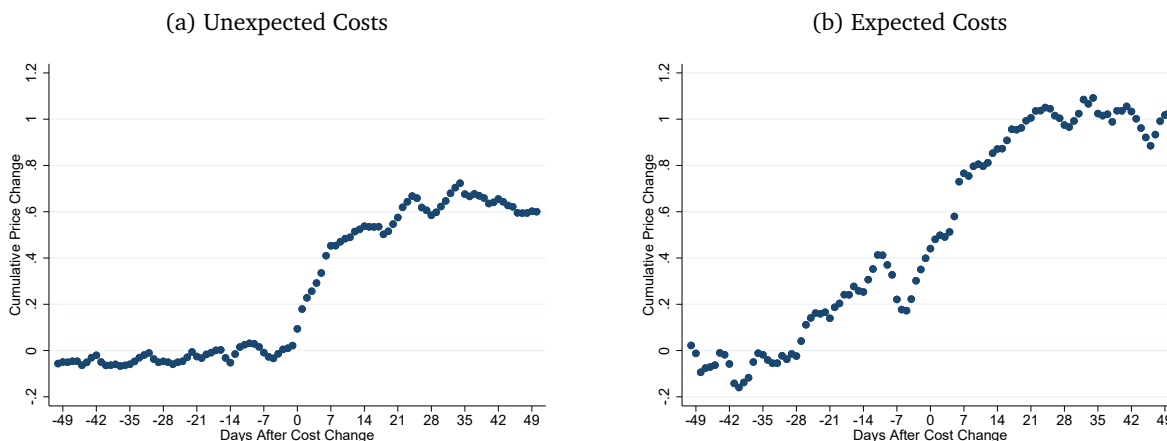
3.3.2 Cost Pass-through

To highlight the temporal component of cost pass-through, we separately estimate how gas stations react to expected versus unexpected cost changes. Beyond motivating the structural model, these results also demonstrate the importance of capturing firms’ anticipated price responses when estimating cost pass-through rates. For example, to analyze how much of a tax increase firms will pass-on to consumers, it is imperative to recognize that firms may begin to adjust their prices prior to the tax increase being enacted; failure to account for this response may lead to underestimating pass-through rates.

We construct our measure of expected cost by using gasoline futures and current wholesale costs to project 30-day-ahead costs. Unexpected costs represent deviations from this projec-

²³This is true with 99 percent confidence for 7 out of the first 8 weeks and with 95 percent confidence for the first week.

Figure 6: Cumulative Pass-through



Notes: Panels (a) and (b) depict the cumulative price change in response to a one unit cost change at time = 0. Response functions are created from the estimated parameters of equation (10).

tion.²⁴ We incorporate the main components of marginal costs for retail gasoline, which include the wholesale cost of gasoline and the per-unit sales tax. We estimate the following model:

$$p_{it} = \sum_{s=-50}^{50} \beta_s \hat{c}_{it-s} + \sum_{s=-50}^{50} \gamma_s \tilde{c}_{it-s} + \sum_{s=-50}^{50} \phi_s \tau_{it-s} + \psi_i + \varepsilon_{it}. \quad (10)$$

Here, p_{it} , is the price observed at gas station i at time t . \hat{c}_{it-s} and \tilde{c}_{it-s} are the expected and unexpected wholesale costs observed with lag s , and τ_{it-s} is the state-level sales tax.²⁵ Using the estimated coefficients on the cost measures, we construct cumulative response functions to track the path of price adjustment to a one time, one unit cost change at time $t = 0$. We incorporate 50 leads and lags to capture the full range of the dynamic response. We focus our results on unexpected and expected costs, as we do not have enough tax changes in our data to estimate a consistent pattern of response.²⁶

Figure 6 plots the cumulative response functions for unexpected and expected costs. Panel (a) displays the results for unexpected costs. Prices react suddenly and quickly at time zero, but it takes about four weeks for the prices to reach the new long-run equilibrium, reaching a peak of 0.71 after 34 days.

Panel (b) displays the cumulative response function for expected costs. Notably, firms begin to react to expected costs approximately 28 days in advance, with a relatively constant adjustment rate until the new long-run equilibrium is reached 21 days after the shock. Though the

²⁴For details, see Section B.1 in the Appendix.

²⁵To more easily incorporate future anticipated costs into the regression, we do not estimate an error-correction model (Engle and Granger, 1987), which is commonly used to estimate pass-through in the retail gasoline literature.

²⁶As a robustness check, we also estimated the price response to expected and unexpected costs using the error-correction model, and we found nearly identical results.

total duration of adjustment is longer compared to the unexpected cost shock, the firm incorporates the cost more quickly after it is realized. This coincides with substantial anticipation by the firm; the price already captures about a third of the effect of the expected cost shock the day before it arrives.

A striking result from these estimates is the difference in the long-run pass-through rates. Expected costs experience approximately “full” pass-through – a cost increase leads to a corresponding price increase of equal magnitude. On the other hand, unexpected costs demonstrate incomplete pass-through, moving about only 66 cents for each dollar increase in cost.²⁷

The different response to unexpected and expected costs emphasizes the need for empirical researchers to think carefully about designing proper estimators for pass-through.²⁸ If costs are anticipated, then a pass-through measure that omits leads will only capture a portion of the overall response. Additionally, if a pass-through estimate is to be used for evaluation, it is important to ensure that the estimator relies on a mix of unexpected and expected shocks that translate to the policy under analysis. In our setting, for example, an analysis that used an unexpected cost shock to predict the impact of a gasoline tax rate change would be inappropriate, as the tax change is anticipated and leads to a much greater price response.

4 Empirical Application: Demand Estimation

Given the reduced-form evidence of dynamic demand and supply behavior, we now present the empirical application of the model to the retail gasoline markets described in the previous section. First, we outline our estimation methodology. We divide it in two stages, as demand can be estimated independently of the supply-side assumptions. Our method of demand estimation relies on data that is widely used in static demand estimation: shares, prices, and an instrument. After outlining the methodology, we present results for demand estimation. In Section 5, we use the estimated demand system to analyze the dynamic incentives faced by suppliers. We use these results to consider a merger between large gasoline retailers.

4.1 Demand Estimation Methodology

Using the dynamic extension of the logit demand system detailed in section 2, we obtain the familiar expression for the log ratio of shares of unaffiliated consumers from equation (2):

$$\ln s_{jt}(0) - \ln s_{0t}(0) = \delta_{jt} \tag{11}$$

²⁷Readers might wonder about the relevance of asymmetric pricing, i.e., whether the price response is the same for positive and negative cost shocks. In robustness checks, we find little evidence of asymmetry.

²⁸An important consideration for pass-through when analyzing imperfect competition is the distinction between idiosyncratic costs and common costs. We address this issue in Appendix B.2.

Likewise, we obtain the following relation for the shares of affiliated consumers:

$$\ln s_{jt}(i) - \ln s_{0t}(i) = \delta_{jt} + \sigma_{jt}(i) \quad (12)$$

We can combine equations (11) and (12) to obtain the following:

$$\ln s_{jt}(i) - \ln s_{0t}(i) - (\ln s_{jt}(0) - \ln s_{0t}(0)) = \sigma_{jt}(i) \quad (13)$$

Thus, we obtain a relationship between purchasing patterns that depends only on the affiliation shock. Empirically, we may parameterize $\sigma_{jt}(i)$ as a function of underlying “dynamic” parameters and the data.

4.1.1 Identification of Choice Distributions

A key challenge with aggregate data and unobserved heterogeneity is that we do not separately observe choice patterns by unobserved consumer type. In our context, we observe the aggregate share, S_{jt} , which is a weighted combination of the $\{s_{jt}(i)\}$ and depends on the distribution of affiliated consumers for each product $\{r_{jt}\}$. Observed shares are determined by the following:

$$S_{jt} = (1 - \sum_k r_{kt}) \cdot s_{jt}(0) + \sum_i r_{it} \cdot s_{jt}(i).$$

To separate out $s_{jt}(i)$ from S_{jt} , we leverage the structure of the model. With discrete types, we show exact identification of the choice distribution without supplemental assumptions.

Proposition 1 *With discrete types, the distribution of choice patterns is identified conditional on the distribution of types and type-specific shocks.*

To show identification, we use the relations in the previous subsection to obtain the following expressions:

$$s_{jt}(0) = \left(\frac{s_{0t}(0)}{s_{0t}(j)} - 1 \right) \frac{1}{\exp(\sigma_{jt}(j)) - 1}$$

$$s_{jt}(i) = s_{0t}(i) \frac{s_{jt}(0)}{s_{0t}(0)} \cdot \exp(\sigma_{jt}(i))$$

That is, the $J + J^2$ unknowns $\{s_{jt}(i)\}$, can be expressed in terms of the $J + 1$ unknowns $\{s_{0t}(j)\}$ and $s_{0t}(0)$.

The observed share equation gives us J restrictions:

$$S_{jt} = (1 - \sum_k r_{kt}) \cdot \left(\frac{s_{0t}(0)}{s_{0t}(j)} - 1 \right) \frac{1}{\exp(\sigma_{jt}(j)) - 1} \\ + \frac{s_{jt}(0)}{s_{0t}(0)} \cdot \sum_i r_{it} \cdot s_{0t}(i) \exp(\sigma_{jt}(i))$$

And the final restriction, $1 - \sum_k s_{jt}(0) - s_{0t}(0) = 0$ identifies the shares $\{s_{jt}(i)\}$, conditional on the parameters θ governing $\{r_{jt}\}$ and $\{\sigma_{jt}(i)\}$, i.e., the unobserved heterogeneity parameters.

4.1.2 Computational Simplicity in Estimation

Though the distribution of unobserved choices is identified, solving for the pattern of choices in estimation is another matter. The traditional approach is to “concentrate out” the distribution of unobserved heterogeneity while using a contraction mapping to solve (implicitly) for the shares of the type 0 consumers (as in Berry et al. (1995)). In our setting, the assumption of single-product affiliation allows us to reduce the computation burden, as the full distribution of choice patterns in each market can be calculated directly after solving a system of equations in two variables. Thus, we reduce the number of unknowns in each market from J to 2. This may be used to speed up estimation by implementing a non-linear equation solver or a (modified) contraction mapping.

Above, we showed that the choice patterns can be expressed in terms of the $J+1$ parameters $\{s_{0t}(j)\}$ in each market. We now show that the system reduces to two parameters in each market, where the remaining $J-1$ parameters are solved for by a quadratic function.

Under the assumption of single-product affiliation, we obtain

$$\sum_i r_{it} \cdot s_{0t}(i) \exp(\sigma_{jt}(i)) = \sum_i r_{it} s_{0t}(i) + (\exp(\sigma_{jt}(j)) - 1) r_{jt} s_{0t}(j).$$

Then, we can write

$$0 = [\exp(\sigma_{jt}(j)) - 1] \frac{r_{jt}}{s_{0t}(0)} s_{0t}(j)^2 \\ + s_{0t}(j) \left([\exp(\sigma_{jt}(j)) - 1] (S_{jt} - r_{jt}) + \frac{1}{s_{0t}(0)} \sum_{0,i} r_{it} s_{0t}(i) \right) \\ - \sum_{0,i} r_{it} s_{0t}(i)$$

and solve for $\{s_{0t}(j)\}$ as a quadratic function of dynamic parameters, observables, and the

two market-level parameters $s_{0t}(0)$ and $\sum_{0,k} r_{kt}s_{0t}(k)$.

4.1.3 Identification of the Demand Parameters

From above, we obtain the utility of the unaffiliated (type 0) consumer in each market, $\{\delta_{jmt}\}$. We now discuss identification of the demand parameters. First, we make the standard assumption that the utility is linear in characteristics:

$$\delta_{jmt} = \alpha p_{jmt} + X_{jmt}\gamma + \eta_{jmt}.$$

The utility depends on price, p , which is endogenous, and exogenous covariates X . The exogenous covariates may contain multi-level fixed effects. Using standard instrumental variable arguments, these linear parameters are identified, conditional on the non-linear parameters used to solve for δ_{jmt} .

As we have exact identification conditional on the non-linear parameters, we need to employ additional moments to achieve identification of the nonlinear parameters θ that govern λ_{jt} and $\sigma_{jt}(j)$. In the context of our model, firms can predict serial correlation in demand shocks and, further, can control these demand shocks by altering prices. Given this context, we impose the supplemental moments that any idiosyncratic product-time shocks that are not anticipated by the firm are uncorrelated over time. We construct these residuals after allowing for time period fixed effects, brand fixed effects, and local seasonal patterns. That is, we assume $Corr(\eta_{jmt}, \eta_{jm(t+1)}) = 0$, where, again, $\{\eta_{jmt}\}$ are the residuals after accounting for multi-level fixed effects, including non-parametric time trends and product-specific fixed effects. The residuals may contain real demand shocks or measurement error from our data. To identify θ , we impose that this moment holds within each market, which provides us with sufficient moments to identify our parameters.²⁹

One interpretation of these moments is that the model treats systematic autocorrelation in product-specific demand shocks as endogenous, rather than treating such correlation a feature of an exogenous stochastic process.

4.1.4 Implementation

To implement our estimator, we use a nested regression approach with the following steps:

1. First, pick values for the non-linear parameters θ that govern δ_{jt} and $\sigma_{jt}(j)$.
2. Calculate $r_{jt} = \lambda_{jt}S_{jt-1}$ for all periods except the first.

²⁹One could construct related moments by using lagged prices as instruments, under the assumption that the prices are uncorrelated with the innovation in the demand residual. Using the first three lags of prices produces similar empirical results.

3. In each market, solve for $s_{0t}(0)$ and $\sum_{0,i} r_{it}s_{0t}(i)$ using the non-linear system of equations obtained previously. Find $s_{jt}(0)$ for each firm.
4. Run the regression implied by equation (11) using the $\{s_{jt}(0)\}$ obtained in the previous step to solve for the linear parameters (α, γ) . Calculate the correlation of the residuals $Corr(\hat{\eta}_{jt}, \hat{\eta}_{j(t+1)})$ within each market.
5. Repeat 1-4 to find θ that minimizes the sum of squared correlations.

The regression for equation (11) may involve instrumental variables and the use of panel data methods such as fixed effects. In our empirical application, we make use of both.

The estimation methodology employs two tricks to speed up the computation of the dynamic model. First, the explicit formula for $\{s_{jt}(0)\}$ means that the non-linear solver³⁰ only has to find two parameters, $s_{0t}(0)$ and $\sum_{0,i} r_{it}s_{0t}(i)$, for each market-period. The quadratic form for the remaining unknowns results in fast calculation. Second, the linear form for the nested regression allows for a quick calculation of the inner part of the routine and allows for serial correlation in unobservables.

In practice, λ_{jt} may not be parameterized in a way that is sufficiently flexible to match the data. For example, if affiliated consumers are highly inelastic, then we should expect $S_{jt} \geq r_{jt}$, as a firm can expect to (at least) retain all of its affiliated customers. If the data have a few instances where shares for a certain product fall precipitously from one week to the next ($S_{jt} \ll S_{jt-1}$), then the implied value of λ_{jt} is low and a parsimonious representation of λ_{jt} may not be able to capture these dynamics. One could consider adding a stochastic term to the affiliation rate or adding a measurement error component to shares to account for this variability. In our application, we impose an ad hoc assumption, adjusting r_{jt} in such instances to the implied value based on the realized share and the average ratio of r_{jt} to S_{jt} across other observations. We add a penalty to the objective function for observations that need this adjustment.

4.2 Data for Structural Model

We supplement the EIA-adjusted weekly brand-county share measures with the average prices for the brand in a week-county. To reduce the occurrence of zero shares, which do not arise in the logit model, we use a simple linear interpolation for gaps up to four weeks. For any gap greater than four weeks, we assume the station was not in the choice set for that gap. We drop any observations that have missing prices, missing shares, or missing shares in the previous week. This includes dropping the first week of data, for which we do not have previous shares.

To reduce the sensitivity of the analysis to brands with small shares and to make the counterfactual exercises more computationally tractable, we aggregate brands with small shares into

³⁰To solve for these unknowns, we use a modified contraction mapping that uses the average of the previous guess and the implied solution for the two parameters in each market. This modification improves stability.

Table 4: Summary Statistics by County

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	N
Num. Brands	4.42	1.51	1	3	5	8	252
Price	2.87	0.11	2.69	2.77	2.95	3.14	252
Wholesale Price	2.25	0.05	2.12	2.21	2.28	2.44	252
Margin	0.21	0.06	0.06	0.17	0.24	0.44	252
Num. Stations	22.56	28.33	1.12	7.00	25.48	243.47	252

Notes: Summary statistics calculated at the market level.

a synthetic "fringe" brand. We designate a brand as part of the fringe if it does not appear in ten or more of the 252 markets (counties). Additionally, if a brand does not make up more than 2 percent of the average shares within a market, or 10 percent of the shares for the periods in which it is present, we also designate the brand as a fringe participant for that market. These steps reduce the number of observations from 194,275 down to 112,929. Additionally, this reduces the maximum number of brands we observe in a county to 8, down from 24. Across all markets, we analyze the pricing behavior of 16 brands, including the synthetic fringe.³¹

Table 4 provides summary statistics of the data for the 252 counties in KY and VA. There is variation in the number of brands we observe in each county, ranging from 1 to 8. There is cross-sectional variation in wholesale prices, margins, and the number of stations in each county.

We also take steps to reduce measurement error in the number of stations in our data. We assume that stations exist for any gaps in our station-specific data lasting less than 12 weeks. Likewise, we trim for entry and exit by looking for 8 consecutive weeks (or more) of no data at the beginning or end of our sample.

4.3 Results: Demand Estimation

For the empirical application, we implement the methodology described in Section (4.1). Conditional on dynamic parameters, we extract the unobserved shares for all unaffiliated type consumers, obtaining the baseline utility δ_{jmt} . We then estimate demand using the typical logit regression. Our chosen dynamic parameters minimize the average correlation in brand-market shocks over time (between contemporaneous and a single-period lag), where the correlation is calculated within each market.³²

³¹Summary statistics by brand are presented in Table 15 in the Appendix. The fringe brand is, on average, 14 percent of the shares for the markets that it appears in. As we designate a fringe participant in nearly every market, the aggregated fringe has the highest overall share (12 percent).

³²In the estimated model, the implied correlation in shocks is -0.01.

Our regression equation takes the following form:

$$\ln(s_{jmt}(0)/s_{0mt}(0)) = \alpha p_{jmt} + \pi(p_{jmt} \times Income_{jmt}) + \gamma N_{jmt} + \phi_t + \zeta_{jm} + \psi_{m,month(t)} + \eta_{jmt}$$

Here, the subscript m denotes the market (county). We have shares and prices at the brand-county-week level. Within-county shares of unaffiliated consumers depend on prices, station amenities,³³ and demographic characteristics of the local population. The brand-county fixed effects, ζ_{jm} , control for variation in the number of stations, brand amenities, and local demographic characteristics. Because we observe station entry and exit, we also include the number of stations for the brand in that market, N_{jmt} , to capture within-brand-county variation over time in this variable.

Thus, brand-county fixed effects, which are identified by the panel, allow us to account for a first-order component of heterogeneity in preferences. Another important component of preferences in this model is price sensitivity. To account for heterogeneity in price sensitivity, we interact price with the median household income of consumers near a brand's stations.³⁴ We do not control for unobserved heterogeneity in price sensitivity, which would add a significant computational burden. Our results suggest that accounting for such heterogeneity, in addition to what we capture, might not be important.

In addition to the brand-county fixed effects, we employ panel data methods to address other unobservables. We allow for the fact that δ_{jmt} may be correlated over time in ways not dependent on (p, N, ζ) . We let the time-varying unobserved components of demand be specified as $\phi_t + \psi_{m,month(t)} + \eta_{jmt}$. That is, we estimate period (weekly) fixed effects $\{\phi_t\}$ and county-specific (monthly) seasonal demand shocks $\{\psi_{m,month(t)}\}$.³⁵ Once we incorporate these fixed effects, the identifying restriction for the dynamic parameters is that the brand-market-period specific shock η_{jmt} is uncorrelated across periods, after accounting for aggregate period-specific shocks, county-level seasonal patterns, and brand-county level differences.³⁶

We allow for endogeneity in pricing behavior by instrumenting for p_{jmt} with deviations in wholesale costs arising from crude oil production in the US. The instrument (z_1) is constructed from a regression of deviations of wholesale costs (from the brand-county average) on the interaction of US production of crude oil with the average wholesale cost for the brand in the county.³⁷ This gives us brand-county-specific time variation in our instrument which is

³³Station amenities include, for example, the presence of food (snack or restaurant), co-location with a super-market, car services, and proximity to an interstate. Demographic characteristics might include median household income, population, population density, and commute percent. These do not vary much over time in our sample; when a new station enters or exits, the averages within a brand do change slightly.

³⁴More explicitly, we take the median household income for the Census tract of each station, and we average these values across stations within a brand. The average is weighted by the population in each Census tract.

³⁵We benefit from the size of our dataset. 95 percent of county-months have at least 16 observations, and 98.5 percent of county-brands have at least 40 observations.

³⁶As mentioned previously, one interpretation of our decomposition is that we attribute all of the brand-specific correlation in demand over time within a market to unobservable demand types arising from affiliation.

³⁷Our measure of the average brand-county wholesale cost is the fixed effect obtained by a regression of wholesale

(a) correlated with the wholesale cost and (b) plausibly not linked to demand. We chose this measure, rather than instrumenting directly with brand-state wholesale costs, to allow for the possibility that local variation in wholesale costs over time may reflect brand-specific demand shocks.

We interact the above instrument with $Income_{jmt}$ to create a second instrument, z_2 , to account for the endogeneity of $(p_{jmt} \times Income_{jmt})$. Both US crude oil production and income are plausibly exogenous with respect to local, time-varying demand shocks. Figure 11 summarizes the time-series variation by plotting mean total market shares and mean prices during our sample in panel (a). In Panel (b), we plot the mean instrument z_1 against the mean price. As the figure shows, there is a strong correlation with the instrument, constructed from US production of crude oil, and prices. Prices display seasonal patterns, reflecting demand, while our instrument does not.

We parameterize the dynamic parameters λ_{jmt} and $\sigma_{jmt}(j)$ as follows:

$$\lambda_{jmt} = \frac{\exp(\theta_1 + \theta_2 Income_{jmt} + \theta_3 Density_{jmt})}{1 + \exp(\theta_1 + \theta_2 Income_{jmt} + \theta_3 Density_{jmt})}$$

$$\sigma_{jmt}(j) = \bar{\xi} + \bar{\alpha} p_{jmt}.$$

Thus, we allow the rate of affiliation to depend on median household income and (log) population density, which we take a proxy for lifestyle.³⁸ Affiliated customers may receive a level shock to utility $\bar{\xi}$, and they may become less (or more) price sensitive for the affiliated brand. This change in price sensitivity is captured by $\bar{\alpha}$. This specification allows for the possibility that consumer characteristics, as captured by income and population density, affects the propensity for consumers to form habits.

The estimates for the linear parameters are reported in Table 5. The first three columns report coefficient estimates from a logit demand regression using observed shares. The fourth column reports the results for unaffiliated customers from our dynamic model. In the static model, all consumers are assumed to be unaffiliated. We obtain a larger (in magnitude) price coefficient with our dynamic specification, as we separate out affiliated consumers with lower price sensitivities. The number of stations appears to matter about the same for attracting unaffiliated consumers as it does in the static model. After instrumenting and including rich fixed effects, we find that the interaction of price and income is not significant. We interpret this finding to the fact the brand-county fixed effects capture first-order variation in consumer heterogeneity.

We note that the R-squared for the regression with unaffiliated consumers falls in the dy-

costs on brand-county and weekly fixed effects, thereby accounting for compositional differences across time.

³⁸We construct these variables by taking the population weighted average across stations by using the local measures in the Census tract.

Table 5: Demand Regressions: Unaffiliated Customers

	Static Model			Dynamic Model
	(1)	(2)	(3)	(4)
Price	-0.021*** (0.006)	-0.205*** (0.009)	-2.755*** (0.284)	-2.952*** (0.516)
Price \times Income		0.056*** (0.009)	-0.006 (0.006)	-0.009 (0.012)
Number of Stations	0.017*** (0.001)	0.017*** (0.001)	0.068*** (0.006)	0.066*** (0.014)
IV	No	Yes	Yes	Yes
Week FEs			X	X
County-(Month of Year) FEs			X	X
Brand-County FEs			X	X
Observations	112,929	112,929	112,929	112,929
R ²	0.044	0.030	0.835	0.648

Notes: Significance levels: * 10 percent, ** 5 percent, *** 1 percent. The table displays the estimated coefficients for a logit demand system, where the dependent variable is the log ratio of the share of the brand to the share of the outside good. For the first three models, the dependent variable uses observed, aggregate shares. For the fourth model, the dependent variable uses the shares of free agent customers, which are calculated based on the estimated dynamic parameters. Standard errors are clustered at the county level. For the dynamic model, standard errors are calculated via the bootstrap.

dynamic model. This is to be expected, as the transformation of the log ratio of observed shares to unaffiliated shares is a non-affine transformation and will not preserve the measure of R-squared. Specifically, the shares for unaffiliated consumers fall closer to zero, from 14 percent (observed) to 9 percent in the dynamic model, and the majority of the variance in aggregate shares is attributed to the variance in unaffiliated shares. This serves to reduce the R-squared under the log-ratio transformation.

Table 6 reports estimates of the dynamic parameters. The parameters θ_1 , θ_2 , and θ_3 imply that 60 percent of consumers, on average, develop an affiliation for the brand they previously purchased from. The coefficient of 0.135 on income indicates that higher-income consumers are more likely to develop an affiliation, consistent with a habit-formation model where switching costs are increasing in wages. Likewise, the coefficient of 0.078 on population density indicates that consumers in more dense areas are more likely to become affiliated. We interpret this to reflect that urban environments have higher driving costs, which also increase switching costs. Both of these demographic variables are standardized, so each coefficient corresponds to an increase of one standard deviation.

Table 6: Estimated Dynamic Parameters

	Affiliation Rate			Strength of Affiliation	
	<i>Baseline</i> θ_1	<i>Income</i> θ_2	<i>Density</i> θ_3	<i>Level</i> $\bar{\xi}$	<i>Price</i> $\bar{\alpha}$
Coefficient	0.400	0.135	0.078	15.707	2.533
95 Percent CI	[0.31, 0.61]	[-0.05, 0.34]	[-0.01, 0.28]	[15.39, 19.93]	[1.02, 2.56]

Notes: The table displays the estimated non-linear coefficients from the dynamic model. The first three parameters imply that, on average, 60 percent of consumers that purchase develop an affiliation for that brand. Brands located in areas with higher incomes and higher population densities have greater rates of affiliation. The next three parameters show that the level shock to utility for affiliated customers is positive, as expected. The last parameter shows that affiliated customers are less price sensitive. Standard errors are in parentheses and are calculated via the bootstrap.

Table 7: Implied Elasticities from Dynamic Model

Group	Mean	Pctl(25)	Median	Pctl(75)
Unaffiliated	-7.704	-9.040	-7.779	-6.358
Affiliated	-0.000	-0.000	-0.000	-0.000
Weighted	-3.090	-3.697	-2.969	-2.345
Naive (Static)	-6.792	-8.089	-6.780	-5.602

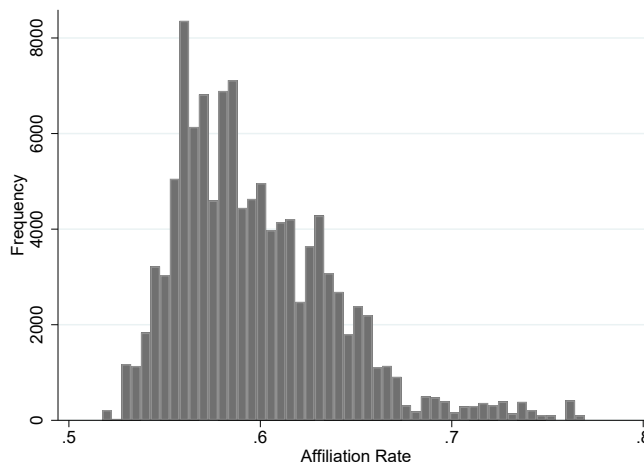
Notes: Table the estimated elasticities for affiliated and unaffiliated consumers. The weighted average elasticity is -3.09, which is less elastic than the estimated elasticity of -6.79 obtained by a static model.

The estimated utility shocks to affiliated consumers, $\bar{\xi}$ and $\bar{\alpha}$, imply that the affiliated consumers are almost completely inelastic with respect to price. To interpret these coefficients, we summarize the implied elasticities in Table 7. The affiliated consumers of our model are very inelastic, with a near-zero response to price effects. The unaffiliated consumers, however, are highly elastic, with an average own-price elasticity of -7.7. This is large in magnitude, and it implies that for a 1 percent increase in price (roughly 3 cents), the station will lose 7.7 percent of the unaffiliated consumers. This high level of price sensitivity for a subset of retail gasoline consumers seems plausible, some “shoppers” have been found to go well out of the way to save a few cents per gallon.³⁹

On average, roughly 40 percent of a brand’s customers come from the unaffiliated pool of consumers in any week in equilibrium. The average weighted elasticity, which weighs affiliated and unaffiliated consumers by their relative (purchasing) proportions, is -3.1. This weighted elasticity is starkly different than the elasticity obtained by estimating the static model. A “naive” estimate (supposing the true model were dynamic) of this elasticity would result in a

³⁹For example, the National Association of Convenience Stores found in their 2018 survey that 38% of people would drive 10 minutes out of their way to save 5 cents per gallon. See, <https://www.convenience.org/Topics/Fuels/Documents/How-Consumers-React-to-Gas-Prices.pdf>

Figure 7: Estimated Heterogeneity in Affiliation Rates



Notes: Histogram represents the empirical distribution of the estimated λ_{jt} parameters.

value of -6.8, which implies a much greater loss in market share for a given price increase than we estimate from the dynamic model. Indeed, the static model obtains an elasticity closer to the unaffiliated elasticity than the overall elasticity from the dynamic model.

One of the features of the model is the ability to capture heterogeneity in affiliation rates. Figure 7 provides a histogram of the affiliation rates across the observations in our sample. There is heterogeneity in our estimates, with high-income, high-density areas realizing affiliation rates as high as 0.75, and low-income, low-density areas having affiliation rates closer to 0.5.

5 Empirical Application: Supply-Side Analysis

5.1 Dynamic Pricing Behavior

Given the demand estimates, we construct the components in each firm's Bellman equation from (5). Using the estimated demand parameters, we are able to recover the (derivative of) the continuation value. The dynamic condition for optimal pricing is:

$$\frac{\partial \pi_{jt}}{\partial p_{jt}} + \beta \frac{\partial E[V_j(r_{t+1}, c_{t+1}, x_{t+1}) | p_t, r_t, c_t, x_t]}{\partial p_{jt}} = 0 \quad (14)$$

Where $\frac{\partial \pi_{jt}}{\partial p_{jt}}$ is the derivative of the per-period profits, which equals $\frac{\partial S_{jt}}{\partial p_{jt}} (p_{jt} - c_{jt}) + S_{jt}$ for single-product firms. The estimation of dynamic parameters, along with our measures of marginal costs, allow for a direct estimate of the derivative of the static profit with respect to price: $\frac{\partial \pi_{jt}}{\partial p_{jt}}$. If this were zero, it would imply that firms are pricing myopically in the context of

Table 8: Summary of Implied $\beta \frac{\partial E[V_j(\cdot)]}{\partial p_{jt}}$

Group	Mean	Min	p25	Median	p75	Max
All	-0.111	-0.760	-0.148	-0.084	-0.046	0.096

Notes: The table displays the estimated derivative of continuation value. A finding of zero would indicate the absence of forward-looking behavior by firms. Negative values indicate that firms are pricing lower in that period than the optimal myopic price.

the model, as they are simply maximizing the current-period profits.

On average, we find that $\frac{\partial \pi_{jt}}{\partial p_{jt}}$ is positive, meaning that firms are systematically pricing lower than the myopic profit-maximizing price. We interpret this as evidence of forward-looking behavior and the presence of dynamics, which is consistent with the reduced-form evidence of Section 3.3.2. Based on equation (14), we attribute the difference between $\frac{\partial \pi_{jt}}{\partial p_{jt}}$ and 0 to be accounted for by the derivative of the continuation value (DCV), $\beta \frac{\partial E[V_j(r_{t+1}, c_{t+1}, x_{t+1}) | p_t, r_t, c_t, x_t]}{\partial p_{jt}}$. That is, the dynamic incentive is the residual that rationalizes the observed pricing behavior of the firms, conditional on the demand-side assumptions, the data, and Bertrand price competition.⁴⁰ After estimating demand in an independent step, we are able to recover these residuals directly.

Summary statistics for the value of the derivative of the continuation value (DCV) are presented in Table 8. The mean and median are negative, which implies that, typically, a reduction in price would increase the expected future return. The magnitudes are significant: the mean of -0.111 implies that a 1 cent increase in price would increase static profits by roughly 4 percent.⁴¹ Intuitively, firms are lowering prices to invest in future demand. This result, combined with our reduced-form findings of anticipatory pricing for expected costs, provides consistent evidence of forward-looking pricing behavior in retail gasoline.

5.2 Supply-Side Estimation

To estimate counterfactual pricing behavior by firms, it is necessary to estimate how dynamic incentives vary with state variables and firm actions. Two approaches are possible. The first is to take a stance on the beliefs of firms and, via forward simulation, solve for the equilibrium continuation value function. Alternatively, one can approximate the DCV with a reduced-form model that is a function of state variables. We pursue the second approach. This greatly reduces computational time to re-compute the price equilibria and avoids the need to make dimension-reducing assumptions (such as constructing a limited grid for prices) that are less palatable in our setting. To accurately represent behavior, this approach requires that the state variables in-

⁴⁰Other explanations may be plausible. For example, a component of this residual may be profits obtained by complementary products, such as food sold at retail gasoline stations.

⁴¹The average (scaled) profit in our data is 0.029. Recall that margins are approximately 21 cents per gallon.

cluded in the reduced-form approximation capture the payoff-relevant states (including market structure) and also that the counterfactual states can be reasonably interpolated from the data.

Using the data and the estimated demand parameters, we obtain estimates of the DCV and project these estimates on prices and state variables, including measures that capture expectations. In general, Markovian assumptions allow for the continuation value to be expressed as a function of the state variables and actions of the firms. We estimate the following dynamic first-order condition:

$$\frac{\partial \pi_{jt}}{\partial p_{jt}} + \Psi_j(p_t, r_t, c_t, x_t; \theta) + \zeta_{jt} = 0 \quad (15)$$

Thus, we use $\Psi_j(\cdot)$ to approximate $\beta \frac{\partial E[V_j(\cdot)|\cdot]}{\partial p_{jt}}$, and ζ_{jt} is the unobserved error. We can use this function to approximate how the dynamic incentives change with the state and the endogenous pricing decisions by firms, allowing for counterfactual analysis. This approach is an alternative to that of Bajari et al. (2007), who use an approximation to the policy function, and, based on this, leverage model structure to estimate the dynamic incentives and static parameters. Conversely, we use structural modeling to obtain static parameters and calculate a reduced-form approximation to the dynamic incentives. One advantage of our approach is that it is not necessary to take a stance on the discount rate or the beliefs of firms; both of these are soaked up by the reduced-form model.

This approach is consistent with a structural model (and solving for the equilibrium DCV) under the assumption that (i) the information set of firms matches the information set of the econometrician and (ii) firms perform limited forecasts of the evolution of the future profits, consistent with the approximation used in estimation. In equilibrium, if firms use a limited set of state variables and a simplified functional form to estimate the dynamic incentives, then the econometrician may be able to replicate the regression (or machine-learning procedure) implemented by firms. In this case, the firms' beliefs can correspond to the econometrician's estimates.⁴²

To estimate $\Psi_j(\cdot)$, we project the residual DCV onto the derivative of shares with respect to prices, the affiliation rate parameter λ_{jt} , marginal costs, expectations of future costs, competition and market structure variables, and the stock of current affiliated consumers. To control for competitive factors, we include the mean stock of affiliated consumers of rivals and the rivals' mean price; both of these are constructed relative to respective variables of the firm. We also include the number of stations, the total number of stations for all brands, and the number of brands as market-level controls. Finally, we interact $\frac{\partial S_{jt}}{\partial p_{jt}}$ with all of the other variables.

Constructing $\Psi_j(\cdot)$ as a function of $\frac{\partial S_{jt}}{\partial p_{jt}}$ and λ_{jt} is motivated by the fact that the marginal effect of price on the stock of affiliated customers in the next period is determined by the interaction of these variables. Thus, to a first-order approximation, we should expect that the

⁴²To get a sense of how close our estimates come to rational expectations, we use forward simulations to check if our estimate of $\Psi(\cdot)$ is consistent with actual DCV, conditional on firms' choosing price according to $\Psi(\cdot)$. We discuss in greater detail in the following section.

derivative of the continuation value moves with the derivative of current period shares. We use λ_{jt} to control for the future value of a marginal consumer today.

Table 9: Dynamic Pricing Incentive: Regressions

	$\beta \frac{\partial E[V_j(\cdot)]}{\partial p_{jt}}$	Sensitivity
	(1)	(2)
$\frac{\partial S_{jt}}{\partial p_{jt}}$	0.250*** (0.001)	-2.474*** (0.019)
λ_{jt}	0.021*** (0.002)	-0.601*** (0.030)
Marginal Cost	-0.004*** (0.000)	0.046*** (0.002)
Cost Change (30-Day Ahead)	0.018*** (0.001)	-0.108*** (0.010)
Mean Price (Rivals)	-0.113*** (0.001)	1.418*** (0.019)
Mean Affiliated (Rivals)	-0.008*** (0.003)	-0.084* (0.043)
Affiliated Customers	-0.958*** (0.004)	12.117*** (0.064)
Market Controls	Yes	Yes
$\frac{\partial S_{jt}}{\partial p_{jt}}$ Interactions	Yes	Yes
Observations	112,929	112,929
R ²	0.952	0.869

Notes: Significance levels: * 10 percent, ** 5 percent, *** 1 percent. The table displays the estimated coefficients from a regression of the dynamic pricing incentive on state variables and the firm's price. The regression includes first-order interactions of all of the displayed variables. The variables are de-meaned, so the coefficient is interpreted as the marginal association at the mean of the other variables. The second column reports the regression with a measure of sensitivity, which is the log absolute value of the dynamic pricing incentive. In general, a negative coefficient in the first column implies a greater sensitivity to dynamics when pricing, generating a positive coefficient in the second column.

The results of estimating equation (15) are reported in Table 9. The first specification reports the coefficients from a regression of the DCV onto the listed variables, additional market

controls, and the first-order interactions with $\frac{\partial S_{jt}}{\partial p_{jt}}$. The variables are de-meaned so that the interpretation of the reported coefficient is the marginal effect at the mean of the other variables. As the DCV is negative on average, a negative coefficient implies that the variable is associated with a stronger dynamic pricing incentive, or a greater deviation from the optimal static price.

To show more directly how sensitive firms are to dynamic considerations, the second column reports a regression where we replace the value of the DCV with the logged absolute value. Thus, the coefficients reflect the semi-elasticity for the magnitude of the dynamic incentive. Typically, a negative coefficient in the first column corresponds to a positive coefficient in the second, as the average value for the DCV is negative.

We find that the derivative of the continuation value with respect to price is positively correlated with the derivative of shares with respect to prices (coefficient of 0.250), which is consistent with our model of consumer affiliation. We also estimate that a higher value of λ is associated with a continuation value that is less sensitive to price. Firms with a higher stock of affiliated customers are more sensitive to dynamic incentives, as indicated by the coefficient of -0.958 . Overall, we find our model, with 20 parameters including a constant, captures over 95 percent of the variation of the residual that rationalizes observed prices.

In general, dynamic models can be sensitive to the choice of functional form and the variables employed in estimation. To verify that our estimate of $\Psi(\cdot)$ is consistent with realized profits, we use forward simulations to calculate the discounted present value of per-period profits when a firm unilaterally deviates its price. For each market and each period, we slightly perturb the price for a single brand. We re-compute shares in that period and then, using our estimate of $\Psi(\cdot)$, calculate equilibrium play in future periods. We use the estimated change in profits to calculate $\beta \frac{\partial E[V_j(\cdot)|\cdot]}{\partial p_{jt}}$ under rational expectations.⁴³ Our estimates are positively correlated with the implied continuation value under rational expectations.⁴⁴

5.3 Horizontal Market Power: Merger Simulation

To evaluate the impact of dynamic pricing incentives on horizontal market power, we simulate a merger between Marathon and BP, which are the number one and number four (non-fringe) brands in terms of overall shares in our sample. Out of the 252 markets, they overlap in 75. In these 75 markets, the average (post-merger) HHI is 1511,⁴⁵ and the mean change in HHI resulting from the merger is 383. In 8 markets, the resulting HHIs are greater than 2500, and

⁴³We simulate forward for 12 periods. We find that the effect on profits dissipates after approximately 9 periods. We use a weekly discount rate of 0.999, which corresponds to an annual discount rate of 0.949.

⁴⁴The mean DCV under rational expectations is 28 percent of the magnitude of the implied residual. It is plausible that profits from complementary goods, which we cannot measure directly, make up the difference. Our reduced-form estimate will pick up the profits from complementary goods as well, which could be considered a feature for the purposes of counterfactual simulation.

⁴⁵As we treat the fringe as a profit-maximizing entity, we calculate HHI treating the fringe as one firm. This will overstate the baseline HHI and the price response by competitors. The change in HHI is unaffected by this abstraction.

Table 10: Merger Effects

(a) Dynamic Model			
Brands	Price	Share	Profit
Marathon-BP	3.33	-13.75	7.33
Other	-0.32	10.37	-6.78
Overall	1.34	-0.47	0.01

(b) Static Model			
Brands	Price	Share	Profit
Marathon-BP	5.87	-21.29	29.77
Other	0.53	4.79	11.75
Overall	2.96	-6.93	20.43

Notes: Table displays the mean effects from a counterfactual merger between two brands in our data. Panel (a) provides the estimates from a dynamic model that accounts for consumer inertia. Panel (b) provides the estimates from a static model that is calibrated to match prices, margins, and shares from the same data. Prices are weighted by the shares observed in the data, i.e., the “no merger” shares.

the changes are greater than 200, meeting the typical thresholds that are presumed likely to enhance market power. The merger would change twelve markets from 3 firms to 2 firms and eighteen markets from 4 firms to 3 firms. We allow the firms to merge⁴⁶ at the beginning of September 2014, and we calculate counterfactual prices⁴⁷ and shares for the second half of our sample.

Our setting, with dynamic brand-specific effects, puts an emphasis on modeling specifically what a merger will be in practice. This can be a nuanced question. Do the merging firms retain separate brands, or do they convert all stations to a single brand? Do affiliated consumers retain their affiliation to the merged company? In our merger counterfactual, we assume that consumer habits are tied to gas station locations and are unaffected by the brand name, and therefore the merging firms retain affiliated consumers from both Marathon and BP.⁴⁸

Panel (a) in Table 10 displays the mean effects of the merger. The effects are modest, with an average price increase for the merging firms of 3.3 percent. Shares for these firms fall by

⁴⁶We combine the merging firms into a single entity and adjust the utility shocks so that the market shares would remain constant at the no merger (share-weighted) prices

⁴⁷Because our inelastic affiliated customers would technically purchase at very high prices, we impose a choke price of \$5 in demand and impose a penalty for prices that exceed this value. The baseline functional form of demand may not be reasonable for extreme out-of-sample values. In our merger counterfactuals, none of the prices approach the choke price.

⁴⁸We consider an alternative scenario where the acquiring firm loses the affiliated consumers from the acquired brand: all of the BP consumers become unaffiliated. Since the one-year post-merger window is sufficient to reach the new long-run equilibrium, the results look similar.

14 percent, and profits increase. Prices for competitors decline slightly, which is not a typical outcome in static price setting models, as prices are usually strategic complements. Prices are strategic substitutes due to affiliation dynamics. When the merging firms raise price, the pool of unaffiliated consumers increases. This increases the average consumer elasticity faced by the non-merging firms, which tends to dampen prices. This effect can outweigh the usual incentive to raise price (arising from the higher price of the merging firms), resulting in lower prices. In aggregate, prices rise by 1.3 percent, and profits barely increase, as most of the extra surplus captured by the merging firms comes at the expense of the rivals.

Overall, these effects are modest relative to what one might expect from a merger with the corresponding share structure (and HHI values). For comparison, we report the results from a merger analysis using a static model in panel (b) of Table 10. The static model is calibrated to use identical prices, margins, and shares, as in the dynamic model.⁴⁹ The static model predicts price effects of over 5 percent for the merging firms. Consistent with the usual merger logic, prices in the static model are strategic complements, as the prices for rivals rise. Overall prices increase by 3 percent, and industry profits increase by 20 percent, which is in stark contrast to the predictions from the dynamic model.

What is driving the results in the dynamic model? Though the merged firm has a static incentive to raise prices, the dynamic incentive is also strengthened, as the firm may accumulate more valuable dynamic assets. Thus, the dynamic incentive to invest in future demand mitigates the incentive to raise prices post-merger, dampening the incentive to exercise horizontal market power.

6 Conclusion

We develop a model of consumer inertia that accounts for commonly observed dynamic pricing behavior, such as the slow adjustment of prices to changes in cost. The dynamics result from competing firms optimally setting prices to consumers that may become loyal or habituated to their current supplier. We show that firms pricing optimally to consumers with dynamic preferences may have higher or lower markups relative to static demand, depending upon whether the incentive to harvest affiliated consumers dominates the incentive to invest in future demand. In this setting, failing to account for dynamic demand will typically cause merger simulations to over-predict post-merger price increases.

Using data from retail gasoline markets, we first demonstrate that prices adjust slowly to cost changes, and that path of price adjustment depends upon whether the cost change is expected or unexpected. This finding demonstrates the importance of accounting for firm expectations when estimating pass-through and in the estimation of demand models that can accommodate dynamics.

⁴⁹The static analysis uses the standard logit discrete choice demand system.

We develop an empirical model that can identify dynamic demand parameters using data on price, shares, and an instrument. Results suggest that 60 percent of retail gasoline consumers become affiliated to the firm from which they currently purchase on a week-to-week basis, and that these consumers are extremely price insensitive. Conversely, we find that unaffiliated consumers are quite price sensitive and play an important role in disciplining equilibrium prices. We evaluate the dynamic incentives affecting prices, and we show, both theoretically and empirically, that merger effects are muted by the presence of dynamic incentives.

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A More Details on Theoretical and Numerical Steady-State Analysis

A.1 Monopoly

We analyze steady-state prices in a monopoly market (with an outside good) to show how habit-forming consumers affect optimal prices and markups.

To simplify notation in the monopoly case, let the monopolist's share of affiliated and unaffiliated consumers be s_j and s_0 , respectively, and its number of affiliated consumers be r . Consumers become affiliated at rate λ . We assume positive dependence in purchase behavior, so that $s_j > s_0$. In the steady state, $r_{jt} = r_{j(t+1)} = r_j$ and $c_{jt} = c_{j(t+1)} = c_j$. The steady-state number of affiliated consumers, r^{ss} , is:

$$\begin{aligned} r^{ss} &= \lambda((1 - r^{ss})s_0 + r^{ss} \cdot s_j) \\ \implies r^{ss} &= \frac{\lambda s_0}{1 - \lambda(s_j - s_0)}. \end{aligned}$$

The steady-state number of affiliated consumers is increasing in the probability of becoming affiliated, λ , and the difference between the choice probabilities of affiliated consumers and unaffiliated consumers, $s_j - s_0$. Using the steady-state value of affiliated consumers, we can solve for the steady-state pricing function.

The steady-state period value is:

$$\begin{aligned} V^{ss}(r^{ss}, c^{ss}) &= (p^{ss} - c^{ss})((1 - r^{ss})s_0 + r^{ss}s_j) + \beta V^{ss} \\ &= \frac{p^{ss} - c^{ss}}{1 - \beta} \cdot \frac{s_0}{1 - \lambda(s_j - s_0)}. \end{aligned}$$

This equation represents the monopolists discounted profits, conditional on costs remaining at its current level. Thus, profits are increasing in both λ and the difference in choice probabilities of affiliated and unaffiliated consumers. These results are straightforward: affiliated consumers are profitable. Also, note that a model with no affiliation is embedded in this formulation ($\lambda = 0$ and $s_j = s_0$), in which case profits are simply the per-unit discounted profits multiplied by the firm's market share.

Maximizing the steady-state value with respect to p^{ss} yields the firm's optimal pricing function:

$$p^{ss} = c^{ss} + \underbrace{\frac{-s_0(1 - \lambda s_j + \lambda s_0)}{\frac{ds_0}{dp}(1 - \lambda s_j) + \frac{ds_j}{dp}\lambda s_0}}_{m = \text{markup of price over marginal cost}}. \quad (16)$$

The second term, m , on the right-hand side of equation (16) captures the extent to which the firm prices above marginal cost (in equilibrium). As this markup term depends upon choice probabilities, it is implicitly a function of price. Thus, as in the standard logit model, we cannot derive an analytical solution for the steady-state price. Nonetheless, we derive a condition below to see how markups are impacted by consumer affiliation. In the usual case, m will be declining in p , ensuring a unique equilibrium in prices.

Are markups higher or lower in the presence of affiliation? When affiliation is absent, $\lambda = 0$ and $s_j = s_0$, equation (16) reduces to the first-order condition of the static model, $p^{ss} = c^{ss} - \frac{s_0}{ds_0/dp}$. Denoting the markup term with affiliation as m_d and the markup term from the static model as m_s , we compare these two terms at the solution to the static model:

$$m_d = -\frac{s_0(1 - \lambda s_j + \lambda s_0)}{\frac{ds_0}{dp}(1 - \lambda s_j) + \frac{ds_j}{dp}\lambda s_0} \gtrless -\frac{s_0}{ds_0/dp} = m_s.$$

For a given price, the terms s_0 and ds_0/dp are equivalent across the two models. Rearranging terms, we obtain a simple condition relating the levels of the markup terms:

$$m_d > m_s \iff -\frac{\partial s_0}{\partial p} > -\frac{\partial s_j}{\partial p}. \quad (17)$$

A higher value for m_d indicates higher markups and higher prices. Thus, if affiliated consumer quantities are relatively less sensitive to changes in price, then markups are higher.

This is an intuitive result. However, there is a nuanced point to this analysis, stemming from the fact that there is not a direct mapping between our assumption of positive dependence and the condition in (17). Given our extension of the logit formulation, $\frac{\partial s_0}{\partial p} = \frac{\partial \delta}{\partial p} s_0(1 - s_0)$ and $\frac{\partial s_j}{\partial p} = (\frac{\partial \delta}{\partial p} + \frac{\partial \sigma}{\partial p}) s_j(1 - s_j)$. Thus, whether or not markups are higher depends on the derivative of the type-specific shock with respect to price and the relative distance of s_0 and s_j from 0.5 (at which point $s(1 - s)$ is maximized). Therefore, steady-state markups may be higher or lower with the presence of consumer affiliation. If we make the additional assumption that affiliated consumer utility is less sensitive to price, i.e. $-\frac{\partial \delta}{\partial p} > -(\frac{\partial \delta}{\partial p} + \frac{\partial \sigma}{\partial p})$, we might expect that markups are higher in the presence of consumer affiliation. However, the results show that it is still ambiguous whether markups are higher in the steady state, as s_j may be close enough to 0.5 relative to s_0 to flip the inequality.

Thus, the presence of positively affiliated consumers may, counter-intuitively, lower the steady-state price, relative to the static model. The intuition for this result is akin to those summarized in Farrell and Klemperer (2007); with dynamic demand and affiliation, firms face a trade-off between pricing aggressively today and “harvesting” affiliated consumers in future periods. In the steady state, our model shows that either effect may dominate.

A.2 Simulation Methodology

The number of unknowns in the system is $J + J + J \times J$, for p , r , and $\frac{dp}{dr}$. The law of motion in the steady state gives us J restrictions ($r = f(p, r)$). This allows us to solve for r given p . p and $\frac{dp}{dr}$ need to be solved for.

We implement the following procedure to solve numerically for the steady state:

1. Provide an initial guess for the matrix $\frac{dp}{dr}$.
2. Using the J restrictions implied by the first-order conditions (one for each product j)

$$\frac{dV_i(r')}{dr'} \cdot \frac{dr'}{dp_j} = -\frac{1}{\beta} \sum_{k \in J_i} \frac{\partial \pi_k}{\partial p_j},$$

solve for $\frac{dV_i(r)}{dr}$. Note that π_k , in this notation, is equal to the sum of profits from all products by a firm.

3. Plug the value of $\frac{dV_i(r)}{dr}$ into the first-order conditions and solve for the steady-state value of p .
4. Take the numerical derivative of p with respect to r . Approximate the numerical derivative by slightly perturbing r : $\tilde{r}_j = r + \epsilon_j$, where j indicates a perturbation in the j^{th} element. Re-solve for p using the first order condition. Calculate

$$\frac{dp}{dr_j} \approx \frac{p^*(r + \epsilon_j) - p^*(r - \epsilon_j)}{2|\epsilon_j|}$$

Stack these vectors horizontally to obtain an approximation for $\frac{dp}{dr}$.

5. Calculate the absolute distance between the approximation of $\frac{dp}{dr}$ calculated in the previous step and the initial guess for $\frac{dp}{dr}$. If this distance falls below a critical value, then the solution is found. If not, update the guess for $\frac{dp}{dr}$ and repeat steps 1-4 above until a solution is found.

A.3 Numerical Simulation Parameters

Table 11: Simulation Parameter Summary Statistics

	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	N
λ	0.43	0.23	0.05	0.25	0.60	0.95	8025
$ \alpha $	6.50	3.56	0.38	3.48	9.26	14.97	8025
$\bar{\alpha}$	3.24	2.79	0.01	0.99	4.90	14.08	8025
ξ	6.54	4.00	-1.96	3.37	9.35	16.59	8025
$\bar{\xi}$	9.86	5.85	0.01	4.69	14.98	19.97	8025

Table 11 displays summary statistics for demand parameters for the 8,025 markets used in the numerical simulations.

A.4 Outcomes and Demand Parameters

Table 12: Simulation: Demand Parameters

	(1) Pre-Merger Price	(2) Price Δ F1	(3) Bias F1	(4) Price Δ F3	(5) Bias F3
λ	0.172*** (0.014)	2.840*** (0.091)	1.839*** (0.026)	0.232*** (0.025)	0.865*** (0.013)
$ \alpha $	-0.135*** (0.003)	-2.730*** (0.018)	-0.285*** (0.005)	-0.526*** (0.005)	-0.200*** (0.003)
$\bar{\alpha}$	0.001 (0.001)	0.016* (0.009)	0.009*** (0.003)	-0.001 (0.003)	0.006*** (0.001)
ξ	0.055*** (0.002)	1.992*** (0.016)	0.241*** (0.004)	0.432*** (0.004)	0.167*** (0.002)
$\bar{\xi}$	0.001** (0.001)	0.004 (0.003)	0.013*** (0.001)	-0.005*** (0.001)	0.007*** (0.000)
Constant	1.359*** (0.003)	4.544*** (0.020)	0.392*** (0.006)	0.525*** (0.005)	0.238*** (0.003)
N	8025	8025	8025	8025	8025

Notes: F1 and F3 refer to firms 1 and 3, respectively. Pre-Merger price is for firm 1. Price Δ and Bias are the merger price change and simulation bias, respectively. All dependent variables are demeaned. Parameters correspond to the dynamic demand model detailed in section 2. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12 in provides results from regressions of pre-merger prices, price changes, and the bias in the static prediction on the demand parameters. On average, these outcomes are increasing in the rate of affiliation and strength of affiliation, as captured by the dynamic paramters. However, these relationships do not hold in every instance, and may interact in interesting ways. As show in Figure 1, prices may be increasing or decreasing in the rate of affiliation. In a small number of markets, we find that the relationship between λ and prices is non-monotonic.

A.5 Numerical Results for Non-Merging Firm

Table 13: Simulation: Merger Price Change and Bias for Non-Merging Firm

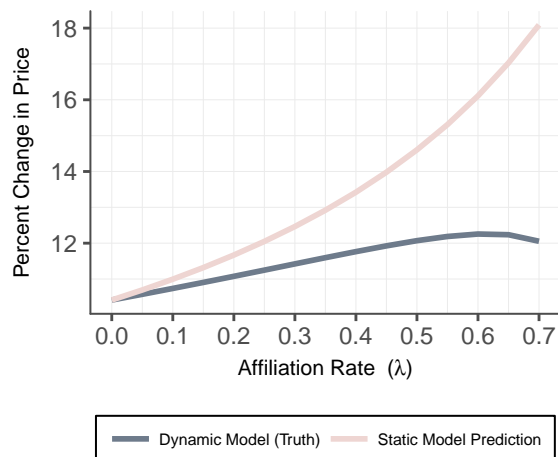
	(1)	(2)	(3)	(4)	(5)	(6)
	Price Δ	Price Δ	Price Δ	Bias	Bias	Bias
Pre-Merger Market Share	6.159*** (0.072)	6.141*** (0.070)	6.136*** (0.069)	2.357*** (0.041)	2.377*** (0.036)	2.382*** (0.035)
Pre-Merger Margin	2.565*** (0.041)	2.532*** (0.040)	2.523*** (0.040)	0.852*** (0.023)	0.889*** (0.021)	0.899*** (0.020)
λ		-0.514*** (0.023)	-0.531*** (0.023)		0.568*** (0.012)	0.587*** (0.012)
$ \frac{\bar{\alpha}}{\alpha} $			-0.064*** (0.018)			0.073*** (0.009)
$\bar{\xi}$			-0.006*** (0.001)			0.007*** (0.000)
Constant	0.525*** (0.006)	0.525*** (0.005)	0.525*** (0.005)	0.238*** (0.003)	0.238*** (0.003)	0.238*** (0.003)
N	8025	8025	8025	8025	8025	8025

Notes: Observations are for firm 3. Price Δ and Bias are the merger price change and simulation bias, respectively. All dependent variables are demeaned. Market share is the aggregate market share. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 presents results for the non-merging firm in the numerical simulations. Results are qualitatively the same as the merging firm, but the estimates are smaller in magnitude. This reflects that the non-merging firm reacts strategically to the merger, but the size of its reaction is less pronounced as it is responding only to the residual demand shock from the merged firm's price change. In the numerical simulations, we find that in 3.8% of observations, the non-merging firm lowers its price in response to the merger. Thus, as in the empirical counterfactual, dynamic affiliation may cause prices to be strategic substitutes.

A.6 Monopoly Prices from Calibrated Static and Dynamic Models

Figure 8: Monopoly Market Power in Static and Dynamic Models



Notes: The plot displays the marginal effects, in terms of mean percent price increase, of a merger to monopoly for different values of λ . The blue line represents the true price increase arising in the dynamic model. The pale line represents the price increase arising in a static model that is calibrated to the same data. The plot reflects 275 baseline parameter values of $(\xi, \bar{\xi}, \alpha, \bar{\alpha})$ that converged for $0 \leq \lambda \leq 0.7$, or 4,125 markets in total.

B Reduced-Form Evidence: Supplemental Results

B.1 Cost Pass-through: Identifying Expected and Unexpected Costs

We now analyze gas stations' dynamic reactions to expected and unexpected costs. To disentangle the reaction to anticipated and unanticipated cost changes, we leverage data on wholesale gasoline futures traded on the New York Mercantile Stock Exchange (NYMEX). The presence of a futures market allows us to project expectations of future wholesale costs for the firms in our market.

To make these projections, we assume that firms are engaging in regression-like predictions of future wholesale costs, and we choose the 30-day ahead cost as our benchmark.⁵⁰ Using station-specific wholesale costs, we regress the 30-day lead wholesale cost on the current wholesale cost and the 30-day ahead future. In particular, we estimate the following equation.

$$c_{it+30} = \alpha_1 c_{it} + \alpha_2 F_t^{30} + \gamma_i + \epsilon_{it} \quad (18)$$

Here, c_{it+30} is the 30-day-ahead wholesale cost for firm i , F_t^{30} is the 30-day ahead forward contract price at date t , and γ_i is a station fixed effect. We use the estimated parameters to construct expected 30-day ahead costs for all firms: $\hat{c}_{it+30} = \hat{\alpha}_1 c_{it} + \hat{\alpha}_2 F_t^{30} + \hat{\gamma}_i$. The unexpected cost, or cost shock, is the residual: $\tilde{c}_{it+30} = c_{it+30} - \hat{c}_{it+30}$.

For robustness, we construct a number of alternative estimates of expected costs, including a specification that makes use of all four available futures. However, we found that these alternative specifications were subject to overfit; the estimates performed substantially worse out-of-sample when we ran the regression on a subset of the data. Our chosen specification is remarkably stable, with a mean absolute difference of one percent when we use only the first half of the panel to estimate the model. Expected costs constitute 74.6 percent of the variation in costs (R^2) in our two-year sample, which includes a large decline in wholesale costs due to several supply shocks in 2014.

A Note on 30-Day Ahead Expectations

One of the challenges in discussing expectations is that they change each day with new information. News about a cost shock 30 days from now may arrive anytime within the next 30 days, if it has not arrived already. Therefore, any discussion of an “unexpected” cost shock must always be qualified with an “as of when.” Given previous findings in the gasoline literature indicating that prices take approximately four weeks to adjust, a 30-day ahead window seems an appropriate one to capture most of any anticipatory pricing behavior. Additionally, our findings support this window as being reasonable in this context. We see no relationship between

⁵⁰Futures are specified in terms of first-of-the-month delivery dates. To convert these to 30-day ahead prices, we use the average between the two futures, weighted by the relative number of days to the delivery date.

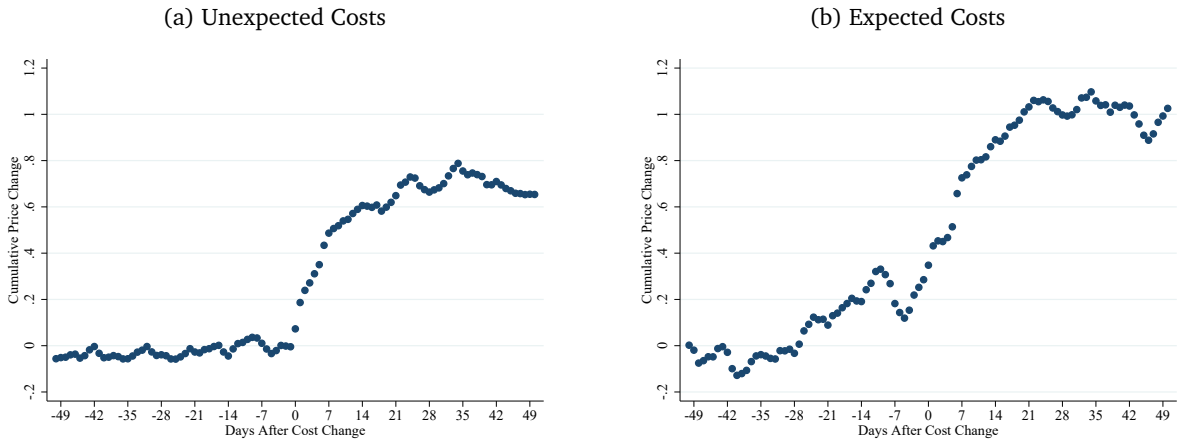
unexpected costs or expected costs and the price 30 days prior.⁵¹

B.2 Pass-through for Common and Idiosyncratic Costs

In subsection 3.3.2, we consider only the simple cut between unexpected and expected costs to focus attention on this previously unexplored dimension of pass-through. Here, we present results for common costs and idiosyncratic costs. In retail gasoline markets, costs are highly correlated, with common costs tending to dominate idiosyncratic costs at moderate frequencies. Therefore, the results for common costs are very similar to those in subsection 3.3.2. One distinction, however, is that pass-through of unexpected common costs is higher than the pass-through for total unexpected costs. For idiosyncratic costs, which we consider by controlling for the prices of rivals, pass-through is on the order of 0.04 to 0.06. This is not surprising for a highly competitive market such as retail gasoline.

In Figure 9, we present pass-through results for common market-level costs. In Figure 10, we present pass-through results controlling for the other firm's prices. Both figures provide results that are consistent with our main estimates.

Figure 9: Cumulative Pass-through for Common Costs



⁵¹We interpret slight deviations from a zero as arising from an underlying correlation in unobserved cost shocks.

Figure 10: Cumulative Pass-through Controlling for Rival Prices

(a) Unexpected Costs



(b) Expected Costs



Table 14: Retail Gasoline in Kentucky and Virginia: Oct 2013 - Sep 2015

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	N
Share	0.141	0.110	0.0003	0.061	0.187	0.688	112,929
Price	2.870	0.529	1.715	2.383	3.310	4.085	112,929
Wholesale Price	2.256	0.527	1.245	1.754	2.673	3.545	112,929
Wholesale FE	2.261	0.031	2.207	2.231	2.293	2.366	112,929
Margin	0.206	0.115	-0.440	0.132	0.273	1.048	112,929
Num. Stations	5.235	7.093	1	2	6	83	112,929
Food	0.859	0.259	0.000	0.803	1.000	1.000	112,431
Supermarket	0.019	0.093	0.000	0.000	0.000	1.000	112,431
Car Service	0.146	0.261	0.000	0.000	0.200	1.000	112,431
Interstate	0.004	0.049	0.000	0.000	0.000	1.000	112,431

C Empirical Application: Supplemental Tables and Figures

C.1 Summary Statistics by Station

Table 14 provides summary statistics for the observation-level data in the analysis. The greatest number of stations a brand has in a single county in our data is 83. The 25th percentile is 2, and we have several observations of a brand with only a single station in our market. The variable Wholesale FE is the average wholesale price for a brand within a county. We interact this variable with the U.S. oil production data to generate an instrument for price in the demand estimation. For the 297 observations that are missing station-specific amenities, we impute the values as the market-period mean.

C.2 Summary Statistics by Brand

Table 15: Summary of Brands

	Brand	Cond. Share	Share	Num. Markets	Num. Stations	Margins
1	Marathon	0.18	0.10	135	5.20	0.21
2	Sheetz	0.18	0.03	37	1.70	0.17
3	Speedway	0.17	0.03	39	3.70	0.18
4	Wawa	0.16	0.01	22	3.20	0.12
5	Exxon	0.16	0.07	119	4.60	0.25
6	Hucks	0.15	0.01	11	1.80	0.15
7	7-Eleven	0.15	0.02	42	6.70	0.18
8	FRINGE	0.14	0.12	244	9.80	0.19
9	Shell	0.13	0.09	165	4.20	0.22
10	Pilot	0.12	0.01	21	1.40	0.13
11	BP	0.12	0.06	127	3.30	0.21
12	Loves	0.11	0.01	15	1.00	0.20
13	Valero	0.11	0.02	59	3.50	0.21
14	Thorntons	0.11	0.00	9	5.90	0.14
15	Sunoco	0.10	0.01	35	4.30	0.29
16	Citgo	0.08	0.01	35	3.90	0.24

C.3 Shares, Prices, and Instrument

Figure 11: Shares and Prices

