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Essays on Dynamic Pricing

by

Koray Cosguner

A dissertation presented to the
Graduate School of Arts and Sciences
of Washington University
in partial fulfillment of the
requirements for the degree
of Doctor of Philosophy

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ABSTRACT OF THE DISSERTATION

Essays on Dynamic Pricing

by

Koray Cosguner

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Professor Tat Y. Chan, Chair

Professor P. B. Seetharaman, Co-Chair

In empirical marketing literature, it is well documented that most of the frequently consumed packaged good categories are governed by inertia that is the phenomenon of consumers often repeat-purchasing the same brand on successive purchase occasions. Under such inertial behavior, market-level demand becomes to be correlated over time, i.e., if the demand of a brand is high in a given week, it is likely to remain high in the ensuing weeks. The pricing implication of such inertia is, for instance, a current retail price cut for a brand not only increase its demand in the current week, but also increase its demand in the ensuing weeks (given that there is no price response from the competitors). Therefore, pricing decisions become dynamic under inertial demand. Even though the phenomenon of inertia has been widely documented at the empirical choice domain, the pricing implications of such inertia have been mostly limited to the analytical area. Therefore, the objective of my dissertation work is to fill this gap in the dynamic empirical pricing domain.

Normative analytical models of oligopolistic pricing account for the fact that in such inertial markets, competing manufacturers have, on the one hand, an incentive to price low in order to invest in building consumer demand for the future, but, on the other hand, an incentive

to price high in order to harvest the reduced price-sensitivity of its existing inertial customers. In Essay 1 of this dissertation, I estimate a structural econometric model of oligopolistic pricing and, on that basis, explicitly disentangle the relative impacts of the two opposing, i.e., investing versus harvesting, incentives on the pricing decisions of cola manufacturers. From our analysis, we find that the net impact of the harvesting and investing incentives in our data is that the equilibrium prices of both brands are lower than those in the absence of inertia (by 4.6% and 3.1% of costs, for Coke and Pepsi, respectively).

Over the past decade, the marketing literature has been enriched by the development of structural econometric models of prices in the distribution channel (Kadiyali, Chintagunta and Vilcassim (2000), Sudhir (2001), Villas-Boas and Zhao (2005), Villas-Boas (2007), Che, Sudhir and Seetharaman (2007), Draganska, Klapper and Villas-Boas (2010)). These models, which derive the wholesale pricing incentives for brand manufacturers, together with the retail pricing incentives for retailers, have typically ignored the existence of *inertial demand*. In Essay 2 of this dissertation, I advance the literature by developing a structural econometric model of prices in the distribution channel in the presence of inertial demand. From our analysis, we find that the net impact of the harvesting and investing incentives in our data is that the channel profit margin of Coke is lower by 3c, while the channel profit of Pepsi is the same as, the corresponding margin in the absence of inertia. We also find the retailer effectively free rides on the manufacturers' efforts by taking a lion's share of the additional profits that accrue to the channel from the existence of inertial demand.

Introduction

Consumers' brand choice behaviors have been widely studied by marketing researchers with respect to frequently consumed packaged good products. Within the choice context, marketing researchers also study the effects of consumers' current choices on their future choices. These studies documented that most of the packaged good categories are governed by inertia that is the phenomenon of consumers often repeat-purchasing the same brand on successive purchase occasions (Allenby and Lenk (1995), Erdem (1996), Roy, Chintagunta and Haldar (1996), Keane (1997), Seetharaman, Ainslie and Chintagunta (1999), Ailawadi, Gedenk and Neslin (1999), Erdem and Sun (2001), Moshkin and Shachar (2002), Seetharaman (2004), Shum (2004), Dube, Hitsch, Rossi and Vitorino (2006)). Such inertial behavior leads to market-level demand to be correlated over time, i.e., if the demand of a brand is high in a given week, it is likely to remain high in the ensuing weeks. The pricing implication of such inertia is, for example, a current retail price cut for a brand not only increase its demand in the current week, but also increase its demand in the ensuing weeks (given that no price response from the competitors). This means the pricing decisions become dynamic once the consumer inertia exists.

Even though the phenomenon of inertia has been widely documented at the empirical choice domain, the pricing implications of such inertia have been mostly limited to the analytical domain. Thus, the objective of this dissertation work is to fill this gap in the empirical pricing domain.

In the analytical domain, there are many studies modeling the pricing decisions of manufacturers under inertial demand (Klemperer (1987a, 1987b), Wernerfelt (1991), Beggs and

Klemperer (1992)), (Chintagunta and Rao (1996), Villas-Boas (2004), Dube, Hitsch and Rossi (2009), Doganoglu (2010)). These *normative* analytical models of oligopolistic pricing account for the fact that in such inertial markets, competing firms have, on the one hand, an incentive to price low in order to *invest* in building consumer demand for the future, but, on the other hand, an incentive to price high in order to *harvest* the reduced price-sensitivity of its existing inertial customers. While some of these papers have emphasized the harvesting incentive (Klemperer (1987a, 1987b), Wernerfelt (1991), Beggs and Klemperer (1992)), others have emphasized the investing incentive (Chintagunta and Rao (1996), Villas-Boas (2004), Dube, Hitsch and Rossi (2009)¹, Doganoglu (2010)). Therefore, empirically estimating the pricing decisions of dynamic manufacturers becomes the next natural step. Essay 1 of this dissertation focuses on this issue, and complements these existing normative studies. In Essay 1, we estimate a structural econometric model of oligopolistic pricing and, on that basis, explicitly disentangle the relative impacts of the two opposing, i.e., investing versus harvesting, incentives on the pricing decisions in the cola market that is characterized by inertial consumer choices at the demand side.

We find that the cola category is characterized by significant inertia in demand, with estimated brand-level switching costs of \$0.30 and \$0.13 for the two consumer segments. Ignoring the investing incentives in manufacturers' dynamic pricing, leads to a sizable (~29% for Coke, ~40% for Pepsi) overestimation, while additionally ignoring the harvesting incentives leads to a smaller, but still sizeable, overestimation (~19% for both brands), in the estimated profit margins of cola brands. The net impact of the harvesting and investing incentives in our data is that the equilibrium prices of both brands are lower than those in the absence of inertia

¹ Similar to Essay 1, Dube et al. (2009) uses an empirically consistent demand specification, but they do not have an econometric estimation of the supply side pricing decisions. Instead of estimating the dynamic pricing decisions as Essay 1, they solve the dynamic pricing equilibrium numerically given the assumed marginal cost.

(by 4.6% and 3.1% of costs, for Coke and Pepsi, respectively). We find that each brand's profit would decrease by 5 % if it were to engage in myopic pricing when its competitor engages in dynamic pricing.

In Essay 1, we show that profits of both brands increase with increasing levels of inertia, with the investing incentive dominating at low to moderate levels of inertia, and the harvesting incentive dominating at high levels of inertia. We also show that increasing the discount factor from 0 to 1 initially increases, and eventually decreases, the profits of both Coke and Pepsi. Finally, we also find that each brand's profits increase in its own discount factor and decrease in its competitor's discount factor, i.e., being infinitely forward-looking is the dominant strategy for both Coke and Pepsi².

After understanding the effects of inertia on manufacturers' pricing decisions, the next natural step becomes understanding the incentives in a full distribution channel. The marketing literature has been enriched, over the past decade, by the development of structural econometric models of prices in the distribution channel (Kadiyali, Chintagunta and Vilcassim (2000), Sudhir (2001), Villas-Boas and Zhao (2005), Villas-Boas (2007), Che, Sudhir and Seetharaman (2007)³, Draganska, Klapper and Villas-Boas (2010)). These models, which derive the wholesale pricing incentives for brand manufacturers, together with the retail pricing incentives for retailers, have typically ignored the existence of *inertial demand*. In Essay 2 of my dissertation, I advance the literature by developing a structural econometric model of prices in the distribution channel in

² The u-shaped relationship between level of inertia and prices has also been shown by the Dube et al. (2009) paper. However, the result of being forward-looking is a dominant strategy for both Coke and Pepsi is a unique finding of Essay 1.

³ Che et al. (2007) models the effect of inertia on pricing decisions in the distribution channel by allowing channel members to be boundedly forward-looking. Therefore, they do not really estimate the fully dynamic pricing game; whereas Essay 2 relaxes this assumption and models the behaviors of the retailer and manufacturers as infinitely forward looking.

the presence of inertial demand. In doing so, we study the relative dynamic pricing implications – representing the *harvesting* versus *investing* incentives of how current price for a brand must optimally take into account, respectively, past versus future demand for the brand – of such inertial demand for brand manufacturers versus the retailer. By doing so, we go beyond the objective of Essay 1, which is how the pricing incentives of manufacturers become different when there is an independent retailer in the picture. In addition to that, we investigate how the incentives of the retailer might be different from manufacturers.

We find that the net impact of the harvesting and investing incentives in our data is that the channel profit margin of Coke is lower by 3c, while the channel profit of Pepsi is the same as, the corresponding margin in the absence of inertia. We also find that while the benefits of the harvesting incentive are almost equally reaped by the manufacturers and the retailer, by appropriately increasing their profit margins, the costs of investing are entirely borne by the manufacturers, by reducing their wholesale profit margins. The retailer effectively free rides on the manufacturers' efforts by taking a lion's share of the additional profits that accrue to the channel from the existence of inertial demand.

A counterfactual simulation reveals that all channel members gain from increasing the level of inertia in the market. The retailer's gain is disproportionately higher than the gains of the manufacturers, and this is in large part because the retailer either does not bear, or bears a relatively minor part of, the increasing costs of investing as the level of inertia increases. Using another counterfactual simulation, we find that the retailer can improve retail profit by as much as 11 % by selling its customer database to the cola manufacturers (at an optimal price) and letting them drop customized price-off coupons to customers belonging to the more price sensitive (less inertial) segment. Interestingly, by engaging in such behavioral price

discrimination, manufacturer profits are lowered, when compared to the case of no price discrimination. Again, the retailer not only entirely benefits from behavioral price discrimination at the expense of manufacturers, but also induces the manufacturers to invest the necessary effort.

1 A Structural Econometric Model of Dynamic Manufacturer

Pricing: A Case Study of the Cola Market

1.1 Introduction

When pricing strategies of product manufacturers recognize the future (i.e., long-term) implications – for consumers and competitors – of their current prices, dynamic manufacturer pricing is said to exist. Such dynamic pricing incentives often arise in product markets which are commonly characterized by *inertia* in consumers' brand choices over time.⁴ Inertia refers to the phenomenon of consumers often repeat-purchasing the same brand on successive purchase occasions. Such inertial, or habitual, brand choice behavior of consumers, in turn, leads to the aggregate (e.g., market-level) demand for a brand being positively correlated over time. In other words, if demand for a brand is high (low) on a given week, it is likely to remain high (low) in ensuing weeks on account of consumer inertia. A pricing implication of such inertia in demand, for example, is that reducing the price of Coke in the current week will increase the demand for Coke not only in the current week but also in the subsequent weeks when the price reduction on Coke has been retracted (assuming no competitive response in prices from other cola manufacturers). Thus, Coke faces a trade-off between charging a low price to attract customers and locking them in, and charging a higher price to extract higher profits from its already locked-in customers. In order to correctly resolve this trade-off when setting price for its brand, Coke must know both (1) the actual extent of inertia in consumers' brand choices in the cola market, as well as (2) the pricing strategies of competing cola manufacturers (such as Pepsi). *Econometrically analyzing historical market-level data on demand and prices of competing cola*

⁴ Economists usually refer to *inertia* using the term *switching costs*.

brands will shed light on (1) and (2). Doing this is the objective of this study. In doing this, the research contribution of our paper is that it estimates a structural econometric model of dynamic pricing decisions of manufacturers in the presence of inertia in consumers' brand choices. Using our estimation procedure, we can study the empirical relevance of various pricing implications that have emerged in the rich analytical literature on normative models of dynamic oligopolistic pricing (which will be explained in detail the next section).

We estimate a consumer-level brand choice model, which includes the effects of inertia, using *scanner panel data* on cola brand choices of consumers in a local market over a period of two years. We then estimate a manufacturer-level oligopolistic pricing model using *retail tracking data* on store-level prices of cola brands from the same local market over the same period of two years. Using a two-segment brand choice model, we find that the cola category is characterized by significant inertia in demand, with estimated brand-level switching costs of \$0.30 and \$0.13 for the two consumer segments. Not accounting for such inertia in brand choices leads to seriously mis-estimated sensitivities of cola demand to marketing mix variables.

We find that ignoring the investing incentives in manufacturers' dynamic pricing, as represented in our dynamic pricing model, leads to a spurious overestimation in the estimated profit margins of 29 % and 40 % for Coke and Pepsi, respectively. Ignoring both the investing and harvesting incentives leads to a spurious overestimation in the estimated profit margins of 19 % for both brands. Estimating a mis-specified demand model without inertia and using it as an input for a static pricing model leads to estimated profit margins that are slightly lower than those implied by the static pricing model that simply sets the inertia parameter to zero among the estimated parameters yielded by a demand model with inertia.

The net impact of the harvesting and investing incentives in our data is that the equilibrium prices of both brands are *lower* (by 4.6 % and 3.1 % of costs, for Coke and Pepsi, respectively) than those in the absence of inertia. In other words, the harvesting incentive -- which increases equilibrium prices of Coke and Pepsi by 2.3 % and 4.2 %, respectively -- is dominated by the investing incentive -- which decreases equilibrium prices of Coke and Pepsi by 6.9 % and 7.3 %, respectively -- for cola brands. We find that each brand's profit would decrease by about 5 % if it were to engage in myopic pricing while its competitor engages in dynamic pricing.

A counterfactual simulation reveals that increasing the discount factor from 0 to 1 initially increases, and eventually decreases, the profits of the two brands. Another counterfactual simulation reveals that each brand's profits increase in its own discount factor and decrease in its competitor's discount factor. A third counterfactual simulation reveals that the investing incentive to pricing dominates at low to moderate levels of inertia, while the harvesting incentive dominates at high levels of inertia. However, profits of both brands steadily increase with inertia.

1.2 Literature Review

In this section, we review three streams of pertinent literature. First, we review the literature on statistical and econometric models of inertial demand. Second, we review the literature on game-theoretic models of dynamic pricing in the presence of inertial demand. Third, we review the emerging literature on structural econometric models of dynamic pricing in the presence of inertial demand.

1.2.1 Statistical and Econometric Models of Inertial Demand

Inertia refers to the positive effect of past purchase of a brand on the consumer's current probability of buying the brand. It can be understood to arise out of consumer habits formed on the basis of prior consumption experiences. One of the early *statistical* models of inertia in consumers' brand choices was proposed by Jeuland (1979), and other statistical models of inertia have been subsequently proposed and estimated over the years (see, for example, Kahn, Kalwani and Morrison (1986), Colombo and Morrison (1989), Bawa (1990), Fader and Lattin (1993), Givon and Horsky (1994), Gupta, Chintagunta and Wittink (1997), Seetharaman and Chintagunta (1998), Seetharaman (2003)).

In recent years, especially since the seminal study of Guadagni and Little (1983), *econometric* models have largely displaced *statistical* models⁵ in being employed to estimate the extent of inertia in consumers' brand choices over time (see, for example, Allenby and Lenk (1995), Erdem (1996), Roy, Chintagunta and Haldar (1996), Keane (1997), Seetharaman, Ainslie and Chintagunta (1999), Ailawadi, Gedenk and Neslin (1999), Erdem and Sun (2001), Moshkin and Shachar (2002), Seetharaman (2004), Shum (2004), Dube, Hitsch, Rossi and Vitorino

⁵ The distinction between *statistical* and *econometric* models is that the latter are grounded in economic theory (Hood and Koopmans 1953).

(2006)). An empirical generalization that has emerged in this literature is that *inertia* overwhelmingly governs consumers' brand choices in packaged goods categories.

In the presence of inertia, a managerial question that arises pertains to the long-term effectiveness of pricing. Seetharaman (2004) shows that ignoring inertia underestimates the total incremental impact of a price reduction by as much as 35%. This suggests that the reduced profit margin for a brand during a period of price reduction may be offset by increases in brand volume not just during the period of promotion but also in future periods. But this finding is predicated on the assumption that competitive price responses from other brands are absent. In reality, however, price changes on a brand would have not only direct effects on its sales, but also indirect effects through the changes triggered in competitive brands' prices. Therefore, a game-theoretic analysis of price competition between manufacturers in markets with inertia would be warranted. We review the existing literature on this subject next.

1.2.2 Game-Theoretic Models of Dynamic Pricing in the Presence of Inertial

Demand

Klemperer (1987a) derives the normative pricing implications of demand inertia in an undifferentiated duopoly using a two-period game-theoretic framework, and shows that the non-cooperative pricing equilibrium in the second period is the same as the collusive outcome in an otherwise identical market without inertia. In other words, two competing firms in a mature market characterized by inertia – each firm with an installed base of customers from the previous period – face demand functions that are relatively price inelastic compared to their counterparts in an otherwise identical mature market without inertia. This decreased price elasticity reduces the price rivalry among the firms, leading to higher prices for the brands of both firms. Klemperer (1987a) also shows that the pricing power that the two firms gain in the second period

leads to vigorous price competition in the first period, which may more than dissipate the firms' extra monopolistic returns from the second period. In other words, in the early growth stages of a market characterized by inertia, competing firms would engage in fierce price competition to build market shares for their brands.

Klemperer (1987b) shows that the central implications of Klemperer (1987a), discussed above, also apply for a differentiated duopoly. Klemperer (1987b) also extends the modeling framework to allow for rational (i.e., "forward-looking") consumers, and shows that first-period prices of the two firms become less competitive because consumers who realize that firms with higher market shares will charge higher prices in the future are less price elastic than naïve consumers.

The two-period game-theoretic models of Klemperer (1987a, 1987b) do not tell us what to expect from price competition over many periods when old (locked-in) customers and new (uncommitted) customers are intermingled and firms cannot discriminate between these groups of customers. Will firms' temptation to exploit their current customer bases lead to higher prices, or will firms' desire to attract new customers lead to lower prices than in the case of no inertia? In order to answer this question, Beggs and Klemperer (1992) extend the duopoly pricing model of Klemperer (1987b) to the infinite period case, where new customers arrive and a fraction of old consumers leave in each period. Beggs and Klemperer (1992) show, over a wide range of parametric assumptions, that firms obtain higher prices and profits compared to those in the absence of inertia. The authors find that prices rise as (1) firms discount the future more, (2) consumers discount the future less, (3) turnover of consumers decreases, and (4) the rate of growth of the market decreases.

In contrast to the discrete-time, game-theoretic framework adopted by Beggs and Klemperer (1992), Wernerfelt (1991) adopts a continuous-time, game-theoretic framework to study price competition between firms in inertial markets. Consistent with the findings in Beggs and Klemperer (1992), Wernerfelt (1991) also derives higher equilibrium prices for firms, as well as a positive effect of the extent of firms' future discounting behavior on equilibrium prices, in inertial markets. This shows that the equilibrium pricing results are robust to whether the game-theoretic pricing models are solved in discrete or continuous time.

As in Wernerfelt (1991), Chintagunta and Rao (1996) also study the normative pricing implications of demand dynamics using a continuous-time, game-theoretic framework. In contrast to Beggs and Klemperer (1992) and Wernerfelt (1991), the authors show, using the estimated extent of inertia in a consumer packaged goods category, that dynamic pricing strategies of firm that recognize the long-run impact of their current prices lead to prices that are 100-200% *lower* than those implied by myopic pricing strategies. In other words, the incentive to the firm of pricing low to *invest* in building consumer demand for the future overwhelms the incentive to the firm of pricing high to *harvest* the reduced price sensitivity of its existing inertial customers (while the latter incentive dominates in the models of Beggs and Klemperer (1992) and Wernerfelt (1991)). The authors also show that in the presence of demand inertia, the firm with the higher baseline preference level will charge the higher price in steady state.

Dube, Hitsch and Rossi (2009) and Doganoglu (2010) obtain normative pricing implications of demand dynamics that are similar to those in Chintagunta and Rao (1996) using discrete-time (as opposed to continuous-time), game-theoretic frameworks. In Dube, Hitsch and Rossi (2009), the dynamic equilibrium is numerically solved for using the estimated inertial demand functions for the orange juice and margarine categories. The authors show that the prices

in the presence of inertia are about 18% lower than the myopic prices in the absence of inertia. Doganoglu (2010) analyzes a dynamic duopoly and shows that when switching costs are sufficiently low, the prices in the steady state are lower than what they would have been when they are absent.

Villas-Boas (2004) analyzes the case where demand inertia in consumers' brand choices endogenously arises out of consumers learning about how well different brands fit their preferences. Using a two-period game-theoretic framework with two firms, Villas-Boas (2004) finds that if the distribution of consumer valuations for each product is negatively skewed, a firm benefits in the future from having a greater market share today. This is an outcome of forward-looking firms competing more aggressively on prices despite the decreased price sensitivity of forward-looking consumers arguing for higher prices than under the myopic case.

To summarize, dynamic pricing strategies for firms facing inertial demand, as derived in the above-mentioned game-theoretic models, are based on resolving the trade-off to the firm between two opposing pricing incentives: on the one hand, the firm has the incentive to price high in order to *harvest* the reduced price sensitivity of its existing inertial customers; on the other hand, the firm has an incentive to price low in order to *invest* in building consumer demand for the future. Which effect dominates the other depends on modeling assumptions. While some papers have emphasized the harvesting incentive (Klemperer (1987a, 1987b), Wernerfelt (1991), Beggs and Klemperer (1992)), others have emphasized the investing incentive (Chintagunta and Rao (1996), Villas-Boas (2004), Dube, Hitsch and Rossi (2009), Doganoglu (2010)).

In contrast to pricing strategy, which is the focus of the above-mentioned literature, Freimer and Horsky (2008) examine the connection between demand inertia and the offering of

price promotions by competing firms in a duopoly. The authors show that for some commonly used price response functions, the existence of demand inertia, at a level of intensity consistent with that identified in empirical research, makes it optimal for competing brands to periodically offer price promotions. It is also shown that competing brands should promote in different periods as opposed to head to head.

Recent advances in econometrics make it possible to estimate the game-theoretic models of dynamic pricing discussed above. We review the emerging literature on this subject next. In fact, this paper adds to this emerging literature stream.

1.2.3 Structural Econometric Models of Dynamic Pricing in the Presence of Inertial Demand

Estimable econometric models of dynamic pricing in the presence of inertial demand require both (1) the solution of discrete-time, stochastic dynamic optimization problems for each firm, where a firm chooses from a continuum of possible prices, and (2) the fixed point to the game-theoretic problem of multiple firms employing their best pricing responses to each other's pricing choices, to be accommodated in the estimation. Such models, referred to as structural models of dynamic pricing in the presence of inertial demand, therefore, present significant computational challenges.

Kim, Klinger and Vale (2003), referred to as KKV henceforth, derive a dynamic pricing model using the first-order conditions of an oligopolistic firm, which is engaged in Bertrand price competition with other firms, in a market with inertial consumers. The firm is assumed to maximize the present value of their lifetime profits, as opposed to just single-period profits. The price-cost margin thus derived includes an additional term beyond that derived under the single-

period profit maximization case (as in, for example, Berry, Levinsohn and Pakes (1995)). This additional term represents the benefit to the firm from capturing customers in the current period that will be “locked in” during future periods, an effect that the myopic pricing model would ignore. Therefore, while the myopic pricing model only presents the incentive to the firm of pricing high to *harvest* the reduced price sensitivity of its existing inertial customers, the dynamic pricing model additionally presents the opposing incentive to the firm of pricing low to *invest* in building consumer demand for the future. In order to empirically uncover the realized trade-offs between the two opposing incentives for firms, Kim, Kliger and Vale (2003) estimate their dynamic pricing model using data on aggregate market shares and price-cost margins of banks. They find that the harvesting incentive dominates the investing incentive for firms in their data. Using a non-structural (i.e., descriptive) pricing model, Viard (2007) finds that decreased levels of inertia, induced by deregulation of the telecommunications industry, decreased prices for toll-free services offered by AT&T and MCI, again seemingly consistent with the harvesting incentive dominating the investing incentive for firms in their data.

Che, Sudhir and Seetharaman (2007), referred to as CSS henceforth, derive a dynamic pricing model using the first-order conditions of an oligopolistic firm, which is engaged in price competition with other firms, in a market with inertial consumers, under two alternative assumptions: (1) Firms engage in Bertrand price competition, (2) Firms engage in tacit price collusion. They estimate the two dynamic pricing models using price data from the breakfast cereals industry. The authors find that omission of inertia in demand biases the econometrician’s inference of manufacturer pricing behavior, i.e., one erroneously infers tacit pricing collusion among breakfast cereals manufacturers when firms are, in fact, competitive. Unlike Kim, Kliger and Vale (2003), who consider infinite future periods, Che, Sudhir and Seetharaman (2007)

assume that the firm is forward-looking over a *finite* number of periods. The authors then find that a two-period dynamic pricing model better explains the observed retail prices of cereals brands than does the one-period myopic pricing model of Berry, Levinsohn and Pakes (1995), as well as a three-period dynamic pricing model. In other words, they show that breakfast cereals manufacturers are boundedly rational, in terms of how far in to the future they look while setting current prices.

While both KKV and CSS represent pioneering research on the estimation of structural econometric models of dynamic pricing in the presence of inertial demand, both papers make restrictive assumptions for the sake of computational convenience (Seetharaman 2009). While KKV rely on estimating *steady-state* pricing equations, CSS, despite correctly estimating *non-stationary* pricing equations, assume a limited time horizon (three periods) of planning for the manufacturers. This assumption is made mainly for computational reasons. In this study, we propose both a fully structural dynamic pricing model, as well as an estimation technique that enables us to recover its parameters. In this sense, we make a key methodological advance to the literature on dynamic pricing. We apply our structural econometric model of dynamic pricing to the cola market. *To reiterate, we propose and estimate, for the first time in the literature, a fully structural econometric model of dynamic pricing in the presence of inertial demand.*

The rest of the paper is organized as follows. In the next section, we present our structural econometric model of inertial demand, as well as the associated estimation procedure. In the third section, we present our structural econometric model of dynamic manufacturer pricing in the presence of inertial demand, as well as the associated estimation procedure. Section 4 presents the estimation results from applying our proposed structural econometric models of inertial demand and dynamic manufacturer pricing on scanner panel data from the cola market.

In Section 5, we discuss the managerial implications of our estimation results based on some counterfactual simulations. Section 6 concludes with caveats and directions for future research.

1.3 Structural Econometric Model of Inertial Demand

To develop a structural econometric model of brand choice with the no-purchase option for scanner panel data in the cola category, we recognize that the typical household h ($h = 1, 2, \dots, H$), which is observed over $t = 1, 2, \dots, T_h$ shopping trips, either buys or does not buy one of J cola brands. On any given shopping trip, we observe an outcome variable y_{ht} that takes the value j ($j = 0, 1, 2, \dots, J$). When $y_{ht} = 0$ it means that the household does not purchase in the cola category during shopping trip t^6 . Further, during each shopping trip of a household, we observe the price (P_{hjt}), display (D_{hjt}), and feature (F_{hjt}) covariates that the household faces, regardless of whether the household purchases in the cola category. Our econometric approach models the multinomial outcome y_{ht} as explained next.

Let U_{hjt} denote the (indirect) utility of household h for brand j at shopping trip t^7 . We assume that we can express this utility as a function of the entire set of brand-specific covariates, ($P_{hjt}, D_{hjt}, F_{hjt}$), as well as the household's lagged brand choice outcome, which represents the

⁶ The reason the no-purchase decision is treated as one of the $J+1$ options is entirely due to computational convenience. However, there is no priori reason to believe that using a different treatment of the outside good will systematically change our results for the supply side analysis. In addition to that, this specification is consistent with the other studies in the structural empirical pricing domain (Sudhir (2001), Che et al. (2007), Dube et al. (2009), etc.).

⁷ Here our assumption is households are myopic utility maximizers. However, we acknowledge that households might be forward-looking in their brand choice behaviors. If that is the case, households make their choices by maximizing their present discounted sum of utilities from a longer time horizon rather than maximizing a single period utility. There can be multiple sources of such forward-looking behavior. For example, if the inertia is not exogenous as assumed here, i.e, if households can control inertia, households can be forward-looking. Even though, that is a possibility, the behavioral literature on inertia (Howard and Sheth (1969)) excludes this kind of strategic behavior. That literature documents inertia as the routinized and low-involvement purchase behavior of households. This definition assumes households as boundedly-rational decision makers. Therefore, given the behavioral explanation of inertia, assuming households to be strategic becomes internally contradictory. Another source of forward-looking behavior might be the stockpiling behavior of households. In this case, consumers might have expectations about future prices and promotions, and they can change their purchase decisions by taking these expectations into consideration. For example, they might order more today and stockpile for the future if there is a promotion. In the same line, they might postpone their purchases if they expect a price promotion in the upcoming periods. Although this kind of strategic behavior is quite possible and well documented in the literature, we do not see significant evidence of such purchase acceleration and stockpiling behavior in our data set (see Appendix 3).

brand that was most recently purchased by the household, also referred to as the household's *state variable*, s_{ht} , as follows.

$$U_{hjt} = \alpha_{hj} + \beta_{1h}P_{hjt} + \beta_{2h}D_{hjt} + \beta_{3h}F_{hjt} + \lambda_h I[S_{ht} = j] + \varepsilon_{hjt}, \quad (1)$$

where α_{hj} , $j = 1, 2, \dots, J$, are the household's brand intercepts, $\beta_h = (\beta_{1h}, \beta_{2h}, \beta_{3h})$ are the household's marketing mix sensitivities, $I[A]$ is the indicator function that takes the value of 1 when event A occurs and the value of 0 otherwise, and λ_h is the household-specific inertia parameter.⁸ We assume that the random errors $\varepsilon_{ht} = (\varepsilon_{h1t}, \varepsilon_{h2t}, \dots, \varepsilon_{hJt})$ are distributed *iid* Gumbel with location 0 and scale 1.

Let U_{h0t} denote the (indirect) utility of household h for the no-purchase option (also called "outside good") 0 at shopping trip t . We assume that we can express this utility as follows.

$$U_{h0t} = \varepsilon_{h0t}. \quad (2)$$

We assume that the random error ε_{h0t} is distributed *iid* Gumbel with location 0 and scale 1.

We determine the multinomial outcome y_{ht} in the usual way: by the principle of maximum utility. We observe the outcome $y_{ht} = j$ when the utility of the j^{th} option to the household exceeds that of the remaining options. This yields the following probabilistic model for brand choice.

$$P_{hjt} = \frac{e^{\alpha_{hj} + \beta_{1h}P_{hjt} + \beta_{2h}D_{hjt} + \beta_{3h}F_{hjt} + \lambda_h I[S_{ht} = j]}}{1 + \sum_{k=1}^J e^{\alpha_{hk} + \beta_{1h}P_{hkt} + \beta_{2h}D_{hkt} + \beta_{3h}F_{hkt} + \lambda_h I[S_{ht} = k]}}, \quad (3)$$

⁸ This coefficient is more generally referred to as the *state dependence coefficient*, and captures inertia only when it takes positive values; it captures variety seeking when it takes negative values. In this paper, we will refer to the state dependence coefficient as the *inertia parameter* for expositional convenience since it only takes positive values in our cola dataset.

which has the familiar Multinomial Logit (MNL) functional form. This inertial demand model, which has been used, for example, by Seetharaman, Ainslie and Chintagunta (1999), captures inertia as a *first-order* behavioral phenomenon, i.e., only the household's most (and not the second-most, third-most etc.) recent brand choice influences its current brand choice probabilities. This assumption is reasonable given that past research in packaged goods categories has demonstrated that higher-order lagged brand choices capture little additional explanatory variance beyond the most recent lagged choice outcome, in terms of explaining current brand choices of consumers (see, for example, Kahn, Kalwani and Morrison 1986, Seetharaman 2003 etc.).

The objective of the empirical analysis is to estimate the parameters $\Psi = (\{\alpha_{hj}, j = 1, 2, \dots, J\}, \{\beta_h = (\beta_{1h}, \beta_{2h}, \beta_{3h})\}, \lambda_h)$ for each of H households.

Following the latent class approach of Kamakura and Russell (1989), we assume that households belong to M segments. This simplifies our empirical objective to estimating the parameters Ψ for each of M segments (rather than H households), as well as the associated segment sizes. This is done by maximizing the following sample log-likelihood function (which has a convenient closed-form expression).⁹

$$\ln L = \sum_{h=1}^H \ln \left(\sum_{m=1}^M \pi_m \left[\prod_{t=1}^{T_h} \prod_{j=1}^J \{P_{mjt}\}^{Y_{hjt}} \right] \right), \quad (3)$$

where $\pi_m \in [0, 1]$ stands for the size of segment m , and P_{mjt} is the conditional MNL probability (obtained by replacing subscript h with subscript m in equation (3)) of household h buying brand

⁹ Unlike the random coefficients logit model, the latent class logit model yields convenient closed-form expressions for aggregate-level brand demand functions (as will be explained in the next section). Further, Andrews, Ainslie and Currim (2002) show that the latent class logit model yields aggregate estimates of brand demand, as well as holdout demand forecasts, that are just as accurate as those yielded by random coefficients logit models.

j at shopping trip t , given that household h belongs to segment m . Since households usually undertake shopping trips at weekly intervals, we will interchangeably use t , for expositional purposes, to refer to shopping trip or week.

1.4 Structural Econometric Model of Dynamic Manufacturer Pricing in the Presence of Inertial Demand

To develop a structural econometric model of manufacturer pricing for retail prices in the cola category, we recognize that each manufacturer j ($j = \text{Coke}, \text{Pepsi}$) sets a price for its brand during each of $t = 1, 2, \dots, T$ weeks in the data.¹⁰ During each week, we observe an outcome variable $P_{jt} > 0$ for each manufacturer. Our econometric approach models the continuous outcome P_{jt} as explained next. We do this in two steps. We first derive a predictive model of aggregate-level brand demand, which is an aggregation of individual-level brand demand, as derived in the previous section. We then embed this predictive model of aggregate-level brand demand within a dynamic pricing game among manufacturers.

1.4.1 Predictive Model of Aggregate-Level Brand Demand

Let S_{jt}^m denote a *state variable* that represents the (segment-specific) *installed base* for brand j during week t . This installed base variable represents the number of consumers in segment m , as of week t , whose most recent brand choice in the cola category is brand j . Further, let $S_t^m = (S_{1t}^m, S_{2t}^m, \dots, S_{Jt}^m)$ represent the vector of installed base variables across all J brands during week t . The following equation, called the *state equation*, captures the evolution of the state variable, S_{jt}^m , from week t to week $t+1$.

$$S_{j,t+1}^m = \sum_{k \neq j}^J S_{kt}^m \text{Pr}_t^m(k \rightarrow j) + S_{jt}^m \left(1 - \sum_{k \neq j}^J \text{Pr}_t^m(j \rightarrow k) \right), \quad (4)$$

¹⁰ While there are 4 brands – Coke, Pepsi, Royal Crown, and Private Label – in the cola category, we endogenize the prices of only the two major brands – Coke, Pepsi – in the empirical analysis. This is done for computational convenience. The prices of Royal Crown and Private Label are treated as exogenous to the analysis.

where $\Pr_t^m(k \rightarrow j)$ stands for the *switching probability*, for a consumer in segment m , of switching from brand k to brand j , and is given by

$$\Pr_t^m(k \rightarrow j) = \frac{e^{\alpha_{mj} + \beta_{1m}P_{hjt} + \beta_{2m}D_{hjt} + \beta_{3m}F_{hjt}}}{1 + e^{\alpha_{mk} + \beta_{1m}P_{hkt} + \beta_{2m}D_{hkt} + \beta_{3m}F_{hkt} + \lambda} + \sum_{l \neq k}^J e^{\alpha_{ml} + \beta_{1m}P_{hlt} + \beta_{2m}D_{hlt} + \beta_{3m}F_{hlt}}}. \quad (5)$$

Equation (4) represents how the installed base of brand j changes from week t to week $t+1$. This happens in two ways (as represented by the two terms on the right-hand side of the equation): one, customers currently in the installed bases of the other brands (S_{kt}^m) switch to the installed base of brand j by buying brand j in week t , which happens with probability $\Pr_t^m(k \rightarrow j)$, as shown in equation (5); two, customers currently in the installed base of brand j (S_{jt}^m) continue being in the installed base of brand j , by either repeat-purchasing brand j , or choosing the no-purchase option, in week t , with the collective probability of the two events being $1 - \sum_{k \neq j}^J \Pr_t^m(j \rightarrow k)$.

Given the state equation (4) governing the evolution of the state variable, S_{jt}^m , aggregate-level brand demand for brand j in week t , D_{jt} , is given by

$$D_{jt} = \sum_{m=1}^M \pi_m * D_{jt}^m, \quad (6)$$

where D_{jt}^m stands for segment-level demand for brand j in week t in segment m , and is given by

$$D_{jt}^m = \sum_{k=1}^J S_{kt}^m * \Pr_t^m(k \rightarrow j). \quad (7)$$

This completes our discussion of the predictive model of aggregate brand-level demand. In summary, aggregate brand-level demand for brand j in week t is predicted using equation (6),

which, in turn requires equation (7) as an input, which, in turn, requires equations (4) and (5) as inputs. The unknown parameters in these equations – which include all parameters in equation (5), as well as the parameter \square_m in equation (6) -- are estimated using household-level scanner panel data, as explained in the previous section.

1.4.2 Markov-Perfect Equilibrium of the Dynamic Pricing Game

Let C_{jt} denote the marginal cost of the manufacturer for brand j during week t . It is written as

$$C_{jt} = C_j + v_{jt}, \tag{8}$$

where C_j stands for a time-invariant marginal cost component (such as average production cost), and v_{jt} is a time-varying cost shock (due to time-varying supply shocks, changes in raw material prices etc.) that is known to the manufacturer (but not to the researcher). We assume that v_{jt} is *iid* $N(0, \sigma_j^2)$ across all j and t . Let $v_t = (v_{1t}, v_{2t}, \dots, v_{Jt})'$.

During week t , each manufacturer is assumed to choose the price for their brand, P_{jt} , with the objective of maximizing the discounted present value of their brand profit over an infinite horizon. This current price, P_{jt} , will not only influence the current demands of brands, D_{jt} , but also change the installed bases of all brands in all consumer segments, S_{jt}^m , which, in turn will affect the future stream of profits of, as well as future strategic interactions among, all manufacturers. All manufacturers are assumed to have full information about the current installed bases of all brands in all consumer segments, $S_t \equiv (\{S_{1t}^m, \dots, S_{Jt}^m\}; m = 1, \dots, M) \in S$, as well as the current cost shocks associated with all brands, $v_t \in Z$. The observed (by the researcher) state vector, S_t , evolves according to the state equation (4) given earlier. In this set-

up, the cost shocks of manufacturers, v_t , do not affect the observed states, S_t , directly. Instead, the cost shocks, v_t , have transitory effects on manufacturers' payoffs by affecting their pricing decisions. In other words, as in Rust (1987), we assume that the observed states, S_t , and unobserved states, v_t , are conditionally independent. The probability transition of the state variables can, therefore, be written as follows.

$$F(S', v' | S, v, P) = \Pr(S' | S, P) * F_v(v'). \quad (9)$$

We assume a discrete-time, infinite-horizon framework (with $t = 1, 2, \dots, \infty$), with manufacturers making simultaneous pricing decisions in each period (week), and playing a repeated Bertrand game with discounting. Under these assumptions, the single-period profit for a manufacturer is given by

$$\Pi^j(P_t, S_t, v_t) = (P_{jt} - C_j - v_{jt}) * D_j(P_t, S_t). \quad (10)$$

Conditional on the current states, S_t and v_t , the manufacturer is assumed to maximize the following expected discounted sum of single-period profits.

$$V_j(S_t, v_t) \equiv \Pi^j(P_t, S_t, v_t) + E \left[\sum_{k=t+1}^{\infty} \rho^{k-t} \Pi^j(P_k, S_k, v_k) | S_t, v_t \right], \quad (11)$$

where the expectation is taken over all competing manufacturers' current actions, all future values of observed and unobserved states, and all future actions of all manufacturers. We also assume that all manufacturers have a common discount factor, $\rho < 1$.

We focus our attention on Pure-Strategy Markov-Perfect Equilibria (MPE), noting that there could be multiple such equilibria. In our case, a Markov strategy for a manufacturer describes their pricing behavior during week t as a function of current states, S_t and v_t . Formally,

each manufacturer's strategy can be written as $\sigma_j : S \times Z \rightarrow P_j \in \mathbb{R}$ for $j = 1, 2, \dots, J$, where P_j is the price charged by manufacturer j . Let $P = (P_1, P_2, \dots, P_J)$ and $\sigma = \prod_{j=1}^J \sigma_j$. The Markov profile $\sigma : S \times Z \rightarrow P$ is a MPE if there is no manufacturer j that prefers an alternative strategy σ_j' over σ_j , when all other manufacturers are choosing their strategies according to σ_{-j} . This can be formally written as follows

$$V_j(S, \nu | \sigma_j, \sigma_{-j}) \geq V_j(S, \nu | \sigma_j', \sigma_{-j}), \forall j, \forall S, \forall \sigma_j'. \quad (12)$$

Given that the behavior is a Markov profile, for each manufacturer i , the discounted sum of profits can be written in the form of the following Bellman equation.

$$V_i(S, \nu) = \sup_{P_i} \pi^i(S, \nu, P) + \rho \int V_i(S', \nu' | P) d \Pr(S' | S, \nu, P) dF_\nu(\nu'). \quad (13)$$

1.4.3 Estimation of the Dynamic Pricing Game

The objective of the estimation is to estimate the marginal cost structure ($\{C_j, \square_j\} j = 1, 2, \dots, J$). In order to achieve this, since the continuation values, $V_j(S, \nu)$, in equation (11) is not known, one first needs to compute the continuation values of the dynamic game for each candidate cost structure. The conventional way of doing this is to compute these continuation values as a fixed point to a functional equation (Rust (1987)). Then, the implied behavior by these continuation values is needed to be matched with the observed behavior. In order to do that, one needs to change the cost parameters until obtaining a close match between the implied and observed behaviors. This requires the fixed point calculation to be repeated hundreds, if not thousands of times. Therefore, the computational burden makes it impossible to use the fixed point algorithm for estimating most dynamic oligopoly games.

Recent literature in industrial organization has emerged proposing techniques to substantially reduce the abovementioned computational burden. The new techniques offered to use the observed data to calculate the continuation values without ever computing the fixed point (Hotz and Miller (1993), Berry and Pakes (2001), Bajari, Benkard and Levin (2007)). However, relying on data to obtain continuation values is not a silver bullet. Despite mitigating the computational burden, obtaining continuation values efficiently requires large data sets creating another challenge to the researcher.

To avoid these pitfalls, we develop a new method to estimate our dynamic pricing game. Our method preserves the benefits of both the fixed point algorithm and the two-step algorithms, while addressing their drawbacks. We explain our estimation method next.

We parameterize manufacturers' pricing policies as flexible functions of state variables, S and ν , as shown below.

$$\hat{P}_j(\theta_j) \equiv f_j(S, \nu | \theta_j), \quad (14)$$

where $\hat{P}_j(\theta_j)$ denotes the parametric approximation of the optimal pricing policies of manufacturer j , $f_j(\cdot)$ is a flexible function (such as a high order polynomial approximation), and θ_j is a vector of parameters characterizing this flexible function. Given the policy function above, as well as the structural parameters, the expected continuation values, $E_{\nu} V_j(S')$, which are represented by the second term on the right-hand side of equation (11), can be computed using forward simulation (see Appendix 1 for details). We take the derivative of the value function in equation (11) with respect to price (from the parametric approximation) in order to construct the first-order conditions, as shown below.

$$\frac{\partial V_j(S, \nu)}{\partial \widehat{P}_j} = \widehat{D}_j + (\widehat{P}_j - C_j - \nu_j) * \frac{\partial \widehat{D}_j}{\partial \widehat{P}_j} + \rho * \frac{\partial E_\nu V_j(\widehat{S}')}{\partial \widehat{P}_j} = 0. \quad (15)$$

where $\widehat{P}_j = \widehat{P}_j(S, \nu)$, $\widehat{D}_j = D_j(S, \widehat{P}_j)$, $\widehat{S}' = S(S, \widehat{P}_j)$. This first-order condition is different from that which corresponds to myopic profit maximization on account of the last term, i.e.,

$\rho * \frac{\partial E_\nu V_j(\widehat{S}')}{\partial \widehat{P}_j}$. This term captures the influence of the current price, \widehat{P}_j , on the next period's

state, \widehat{S}' , and, therefore, on the expected continuation value, $E_\nu V_j(\widehat{S}')$, of the next period. This

term captures the investing incentive of the manufacturer toward lowering the current price, \widehat{P}_j ,

in order to raise the next period's state, \widehat{S}' . In the absence of this term, the only effect of inertia

in demand will be reflected in the harvesting incentive, which is reflected in the second term,

$(\widehat{P}_j - C_j - \nu_j) * \frac{\partial \widehat{D}_j}{\partial \widehat{P}_j}$. The derivative, with respect to price, of the expected continuation value of

the next period, $\frac{\partial E_\nu V_j(\widehat{S}')}{\partial \widehat{P}_j}$, can be obtained using chain rule, as shown below.

$$\frac{\partial E_\nu V_j(\widehat{S}')}{\partial \widehat{P}_j} = \frac{\partial E_\nu V_j(\widehat{S}')}{\partial \widehat{S}'} * \frac{\partial \widehat{S}'}{\partial \widehat{P}_j}. \quad (16)$$

Rearranging terms, we can write the first-order condition for the optimal price P^* as below.

$$P_j^*(S, \nu) = C_j + \nu_j - \left\{ \widehat{D}_j + \rho * \frac{\partial E_\nu V_j(\widehat{S}')}{\partial \widehat{P}_j} \right\} \left[\frac{\partial \widehat{D}_j}{\partial \widehat{P}_j} \right]^{-1}. \quad (17)$$

If the policy function in equation (14) is optimal, for any given set of state variables, (S, ν) , the computed parametric prices should match the optimal prices from the above equation, after allowing for approximation error due to the parametric policy functions, as shown below.

$$P_j^*(S, \nu) - \widehat{P}_j(S, \nu | \theta_j) \cong 0. \quad (18)$$

In order to recover the structural parameters of interest, i.e., C_j and σ_j , we construct the following two moment conditions.

$$E[\nu_j | S] = 0, E[\nu_j^2 | S] - \sigma_j^2 = 0, \quad (19)$$

where ν_j is obtained using the optimality condition for manufacturers, i.e., equation (17), as shown below.

$$\nu_j = P_j - C_j + \left\{ D_j + \rho^* \frac{\partial E_{\nu_j} V^j(S')}{\partial P_j} \right\} \left[\frac{\partial D_j}{\partial P_j} \right]^{-1}. \quad (20)$$

where P is the observed price in the data, $D_j = D_j(S, P)$, $S' = S'(S, P)$. The GMM estimator, as applied in the literature, typically relies on the first moment only. In our case, in order to identify the cost shock variance parameter, σ_j , we additionally use the second moment, as shown in equation (19). A second point of departure of our estimation approach from the GMM estimator that is typically used in the literature lies in equation (18). Given a set of state variables, (S_q, ν_q) , $q = 1, \dots, S$, our estimates are obtained by minimizing not only a criterion function that is based on the moment conditions in equation (20), but also the following “penalty” function.

$$\sum_{q=1}^S \left[P_j^*(S_q, \nu_q) - \widehat{P}_j(S_q, \nu_q | \theta_j) \right]^2. \quad (21)$$

At the true policy functions and true values of model parameters, the moment conditions in equation (20) will be satisfied, while the approximation error in equation (21) will be minimized.

Our estimation approach is similar to a constrained optimization method (MPEC), recently developed by Su and Judd (2011). The MPEC approach also imposes equilibrium

conditions instead of using the fixed point calculation. The MPEC approach minimizes a GMM criterion function subject to the imposed equilibrium constraints by using constrained optimization techniques. For each trial set of parameters in the numerical search, the MPEC approach treats the continuation values (at each state combination, (S, ν)) as a parameter. Our approach is different from the MPEC approach in the following ways: first, our approach uses equilibrium conditions with penalty functions, as shown in equation (21), which do not require exact matches between the parameterized policy functions, $\widehat{P}_j(S_q, \nu_q | \theta_j)$, and the equilibrium policies, $P_j^*(S_q, \nu_q)$. This is because we treat the parameterized policy functions, $\widehat{P}_j(S_q, \nu_q | \theta_j)$, as approximations, that are allowed to deviate from the optimal policies even at true values of parameters. Second, under our approach, only the θ_j 's are additional parameters to be estimated, while under the MPEC approach, $V(S, \nu)$ for all S and ν in the state space, are additional parameters to be estimated. This implies the number of parameters to be estimated under our approach is much smaller compared to the MPEC approach.

It is also worthwhile to compare our approach with Bajari, Benkard and Levin (2007, hereafter BBL) and Berry and Pakes (2001, hereafter BP). As a first step, the BBL approach estimates the policy functions for various state points in the observed space. Then, with these estimated policy functions, they forward simulate the continuation values of manufacturers. By embedding this simulation exercise in a numerical search routine we can estimate the cost structure of our manufacturers. The major limitation associated with this estimation approach is that the sampling error inherent in the first step may be severe. This is especially the case if there are insufficient observations to represent all possible points in the state space. This is indeed the case in our dataset, in which we only have about 100 weekly observations for each manufacturer. This sampling error, in turn, would adversely impact the efficiency of the marginal cost

parameters estimated in the second step. In addition, the BBL approach is inapplicable with multiple unobserved state variables, as in our case, where each manufacturer's pricing decision depends on the cost shocks of all manufacturers. Therefore, adapting the BBL algorithm to estimate our dynamic game becomes infeasible.

Another approach designed to estimate dynamic games like ours is the BP approach. Similar to our proposed approach, BP also use estimation equations derived from first order conditions for the firms' continuous controls. However the implementation of each approach is quite different. First of all, to approximate the continuation values for a given marginal cost structure, BP uses the observed time series data; whereas our approach uses forward simulation by using the parametric policy functions (whose parameters are estimated along with the structural parameters). This means our approach has a much lower data requirement compared to BP. The benefits of this are threefold: unlike the BP approach, 1) the sampling bias due to small data size is no longer an issue for us; 2) the use of forward simulation allows us to average out and get consistent estimates of the continuation values; 3) the truncation error problem no longer exists for our approach, because we do not rely on data to calculate continuation values, thus the length of the time series data does not pose a limitation to our approach.

The asymptotic distribution of our estimator is difficult to derive and even it has a closed form, it is likely to be difficult to calculate (as in BBL). Therefore, we use the following bootstrapping procedure to calculate the standard errors:

1. We draw θ^{Ds} , $s = 1, 2, \dots, ns$, from the asymptotic normal distribution of the demand model parameter estimates, $N(\hat{\Theta}^D, \hat{\Sigma}^D)$, where $\hat{\Theta}^D$ stands for the estimated demand

parameters, and $\hat{\Sigma}^D$ stands for the estimated covariance matrix of the estimated demand parameters.

2. We obtain bootstrapped data, $(P_t^s, S_t^s, s = 1, 2, \dots, ns)$, by drawing independent, random samples, with replacement, from the original data.
3. We re-estimate the parameters of the structural econometric model of dynamic manufacturer pricing for each bootstrapped draw of the original data (from Step 2 above), while generating the evolution of states, S , as well as the demand function, D , based on each bootstrapped draw of the estimated demand model parameters (from Step 1 above).
4. Using the estimated pricing model parameters from Step 3 above, across all bootstrapped draws, we calculate the standard errors associated with those estimates.

Below, we summarize the benefits of our estimation method for multi-agent problems.

1. It is easy to implement and uses the forward simulation idea;
2. It can be used for problems where multiple unobserved states (cost shocks, in our case) enter the policies of economic agents (manufacturers, in our case);
3. It can flexibly model policies as a function of numerous state variables, without being constrained by the number of state space points reflected in the data (unlike BBL);

We conduct a series of Monte Carlo simulations in order to study how well our proposed estimation approach can recover the model parameters under a wide range of assumed structural parameters, i.e., high versus low average cost, high versus low cost shock, using a sample size similar to ours. We also allow for monopoly versus duopoly scenarios in the simulation. Under each tested case in our simulations, we find that the estimates of C_j and σ_j and are very close to

their true (assumed) values. The results are reported in Appendix 3. This Monte Carlo simulation exercise gives us confidence regarding the efficiency of our proposed estimator.

1.5 Empirical Results

We use scanner panel data from Information Resources Incorporated's (IRI) scanner-panel database on cola purchases of 356 households making 32942 shopping trips at a supermarket store in a suburban market of a large U.S. city. The dataset covers a two-year period from June 1991 to June 1993. The supermarket is a local monopolist in the sense of not having other supermarkets nearby and, therefore, drawing a loyal core group of shoppers to the same store for their grocery shopping. Table 1.1 presents some descriptive statistics on weekly marketing variables and market shares of four major cola brands in the data. The 356 households are observed to purchase cola during 5784 (17.56%) of their shopping trips. In terms of average prices, we see that Coke, Pepsi and Royal Crown occupy a high price-tier, while the Private Label occupies a low price-tier, at the store. In terms of display and feature promotions, we see that Pepsi is displayed and featured more frequently than the other brands by the retailer. In terms of average weekly market shares, Pepsi is observed to be the dominant cola brand (with an average market share of 0.4567), while the Private Label is the smallest brand (with an average market share of 0.0685).

1.5.1 Estimation Results for the Inertial Demand Model

Table 1.2 presents the estimates of the inertial demand model under the 2-support heterogeneity specification (which is reported, as well as used as an input for the dynamic pricing model, for expositional convenience).¹¹ As far as the brand intercepts are concerned, we find that the private label has the smallest -- most negative -- value of the estimated brand intercept among the four brands in both segments. This suggests that the private label brand

¹¹ Substantive insights gleaned from our empirical analysis remain similar when the heterogeneity specification is modified to include additional supports for the heterogeneity distribution. These results are available upon request.

enjoys the lowest baseline preference in the cola market, which is not surprising considering that private label brands typically draw sales on account of their lower prices, as opposed to their relative intrinsic attractiveness, when compared to other (national) brands. Pepsi is found to have the highest baseline preference among the four brands in both segments, while Coke has the second highest baseline preference. This is consistent with the institutional reality that Pepsi was the dominant cola brand in supermarket stores (even though Coke had higher overall national market share) in the US during the 1990s.

As far as the marketing mix coefficients are concerned, the estimated price coefficient is negative, as expected, for both segments. This implies that as price of a brand increases, a household's probability of buying the brand decreases. The estimated display and feature coefficients are positive, as expected, for both segments. This suggests that as display or feature advertising for a brand increases, a household's probability of buying the brand increases. Between the two segments, segment 2 (the larger segment, containing 71 % of the households) is found to be more price-sensitive (price coefficient of -6.727 versus -5.233), more display-sensitive (display coefficient of 1.454 versus 1.113), and more feature-sensitive (feature coefficient of 0.320 versus 0.228), than segment 1.

As far as the estimated inertia coefficients are concerned, they are positive for both segments. This implies that after controlling for the effects of a household's intrinsic brand preferences and their responsiveness to the marketing activities of brands, the household's probability of buying the previously purchased brand is higher than the household's probability of buying any of the remaining brands. In order to understand the degree of asymmetry across brands in terms of how much they benefit from the presence of inertia in the category, we calculate the following difference (averaged over all observations in the data), $Pr(j|j) - Pr(j|i)$,

which represents the increase in a household's purchase probability for brand j on account of inertia, for each brand j , where the conditioning event refers to the previously purchased brand, and $Pr(j|i)$ is averaged over all possible i . This turns out to be 0.044, 0.064, 0.028 and 0.014 for Coke, Pepsi, Royal Crown and the Private Label, respectively. In other words, a household's purchase probability for Coke (Pepsi) increases by 0.044 (0.064) when Coke (Pepsi) is the previously purchased brand than when a competing brand is the previously purchased brand. Taken in the context of the four brands' average market shares in the data, which represent brands' average baseline purchase probabilities among all households in the market, the benefits due to inertia translate to percentage increases of 15 %, 14 %, 20 % and 16 %, respectively. Considering each segment separately, the increase in purchase probabilities on account of inertia for Coke, Pepsi, Royal Crown and the Private Label, respectively, turn out to be 0.133, 0.191, 0.085 and 0.027 for segment 1, and 0.008, 0.013, 0.004 and 0.008 for segment 2. In other words, households in segment 1 are more inertial than households in segment 2. The estimated inertia parameters translate to switching costs -- which can be interpreted as the price premium that a brand can charge in the current week to a consumer who bought that same brand last time, relative to a consumer who bought another brand last time -- of \$0.30 and \$0.13 in segments 1 and 2, respectively. These are substantively significant, given the average prices of cola brands (see Table 1.1).

Table 1.3 presents the estimates of a benchmark demand model, again under the 2-support heterogeneity specification, without inertia. The two segments have been ordered to correspond, in terms of their estimated sizes, to the two segments in Table 1.2. First, we notice that the demand model without inertia does not fit the demand data as well as the demand model with inertia (BIC of 29090.12 versus 27624.15), which shows that the estimated degree of inertia

is statistically important. Further, the estimated brand intercepts for all four brands are found to be higher than their counterparts in Table 1.2. This implies that ignoring inertia makes one falsely estimate a higher probability of cola category purchase (relative to the outside good option) for a household. Similar substantive biases manifest in the estimated marketing mix coefficients as well. For example, the magnitude of the estimated price coefficient is overstated in the smaller segment 1 (-6.223 versus -5.233), and understated in the larger segment 2 (-6.544 versus -6.727), when inertia is ignored. The magnitude of the estimated display coefficient is understated in both segments when inertia is ignored. To the extent that the estimated marketing mix sensitivities are critical inputs to the cola brands' marketing mix optimization problems, mis-estimated marketing mix sensitivities yielded by a demand model without inertia will imply different (sub-optimal) profit margins for the cola manufacturers than those yielded by a demand model with inertia. These differences are elaborated upon in the next section.

1.5.2 Estimation Results for the Structural Econometric Model of Dynamic

Manufacturer Pricing in the Presence of Inertial Demand

Table 1.4 presents the estimated marginal costs of production, along with the estimated variances of the cost shocks, for Coke and Pepsi under the proposed structural econometric model of dynamic manufacturer pricing.¹² As a point of comparison, we also present the estimated costs yielded by a *myopic pricing model*, which sets the discount factor for all agents – cola manufacturers, as well as the retailer -- to 0. In other words, the myopic pricing model assumes that prices are set to maximize current period profit, as in, for example, Berry, Levinsohn and Pakes (1995). As a second point of comparison, we present the estimated costs

¹² Again ignoring the strategic aspect of the prices of Royal Crown and the Private Label can be rationalized by the observation in Table 1.1 that they have much smaller market shares than Coke and Pepsi and are, therefore, unlikely to significantly influence the pricing decisions of Coke and Pepsi.

yielded by a *static pricing model*, referred to as *Static1*, which, in addition to assuming that prices are set to maximize current period profit (as under the myopic pricing model), sets the inertia parameter to zero. In other words, under the myopic pricing model, manufacturers do not have the *investing* incentive when making their pricing decisions, while under the static pricing model *Static 1*, they have neither investing nor harvesting incentives. As a third point of comparison, we present the estimated costs yielded by a second static pricing model, referred to as *Static 2*, which is identical to *Static 1*, except that it takes the estimated demand model without inertia as an input to the pricing model. In other words, instead of setting the inertia parameter to zero under the estimated demand model with inertia (as does *Static 1*), *Static 2* uses the estimates from the demand model without inertia. Comparing *Static 2* to the remaining three pricing models allows us to investigate the influence of demand mis-specification on the estimated marginal costs.

We find that the estimated marginal costs for Coke and Pepsi decrease under the myopic pricing model compared to the proposed dynamic pricing model. Specifically, the estimated marginal cost for Coke (Pepsi) is \$0.650 (\$0.593) under the dynamic pricing model and \$0.605 (\$0.531) under the myopic pricing model. This translates to a price-cost margin of \$0.155 (\$0.157) for Coke (Pepsi) under the dynamic pricing model and \$0.200 (\$0.219) under the myopic pricing model. This can be understood as follows: The myopic pricing model allows for the harvesting (pressure to raise price), but not the investing (pressure to decrease price), incentive in driving the firm's pricing decision. Therefore, the optimal price-cost margin that is implied by the myopic pricing model is higher than that implied by a dynamic pricing model. Since both models are estimated using the same observed price data, a higher implied price-cost margin under the myopic pricing model manifests as a lower estimated marginal cost. This

makes intuitive sense. From a substantive standpoint, the differences in the estimated marginal costs are 5c and 6c, for Coke and Pepsi, respectively. In percentage terms, the differences in the estimated profit margins translate to 29 % and 40 %, respectively. In other words, by ignoring the investing incentive of dynamic manufacturer pricing, we over-estimate retail profit margins of Coke and Pepsi by 29 % and 40 %, respectively.

We find that the estimated marginal costs for Coke and Pepsi are lower under the static pricing model, *Static1*, than under the proposed dynamic pricing model, but higher than under the myopic pricing model. Specifically, the estimated marginal cost for Coke (Pepsi) is \$0.621 (\$0.563) under *Static 1*, which translates to a price-cost margin of \$0.184 (\$0.187). This can be understood as follows: When compared to the myopic pricing model, *Static 1* does not allow for the harvesting (pressure to raise price) incentive in driving the firm's pricing decision. Therefore, the optimal price-cost margin that is implied by the static pricing model is lower than that implied by a myopic pricing model. Since both models are estimated using the same observed price data, a lower implied price-cost margin under the static pricing model manifests as a higher estimated marginal cost than under the myopic pricing model. This makes intuitive sense. From a substantive standpoint, the differences in the estimated marginal costs between the dynamic pricing model and the static pricing model, *Static1*, are 3c for both brands. In percentage terms, the differences in the estimated profit margins translate to 19 % for both brands. In other words, by ignoring both the harvesting and investing incentives of dynamic manufacturer pricing, we over-estimate retail profit margins of Coke and Pepsi by 19 % each

To summarize the results above, ignoring only the investing incentive, but not the harvesting incentive, over-estimates profit margins of Coke and Pepsi by 29 % and 40%, respectively; on the other hand, ignoring both the harvesting and investing incentives over-

estimates the profit margins of both brands by only 19%. The reason for this finding is as follows: The direction of the bias in the estimated marginal cost of a brand that results from ignoring the investing incentive is negative (i.e., toward zero); the direction of the bias from ignoring the harvesting incentive is positive (i.e., away from zero); therefore, the net effect of the two opposing biases that result from simultaneously ignoring both investing and harvesting incentives, is to yield estimated profit margins of brands that are closer to the profit margins that are yielded by the dynamic pricing model.

Last, we find that the estimated marginal costs for Coke and Pepsi are lower under the static pricing model, *Static2*, than under the proposed dynamic pricing model, but higher than under the myopic pricing model and the static pricing model, *Static1*. Specifically, the estimated marginal cost for Coke (Pepsi) is \$0.635 (\$0.569) under *Static 2*, which translates to a price-cost margin of \$0.170 (\$0.181). The difference in the estimated marginal costs between the two static pricing models, *Static1* and *Static2*, is purely attributable to mis-specification biases in the estimated demand parameters that are used as inputs in the pricing model. While both *Static1* and *Static2* set the inertia parameter to zero, *Static 1* relies on Table 1.2, while *Static 2* relies on Table 1.3, for estimates of the remaining demand parameters. A comparison of Tables 1.2 and 1.3 makes clear that the estimates of the remaining demand parameters (i.e., brand intercepts and marketing mix coefficients) are significantly different between *Static 1* and *Static 2*. This explains why the estimated costs are different between *Static1* and *Static2*.

1.6 Managerial Implications

In order to understand the substantive implications of our estimated structural econometric model of dynamic pricing, we use the estimated structural parameters for the proposed dynamic pricing model (from the second column of Table 1.4) and compute the equilibrium prices for Coke and Pepsi that would result from myopic pricing (which ignores the investing incentive), as well as from static pricing (which ignores both the investing and harvesting incentives). The results of these computations are reported in Table 1.5. Under static pricing, the equilibrium profit margins of Coke and Pepsi are \$0.183 (28%) and \$0.184 (31%), respectively. Under myopic pricing, the equilibrium profit margins of Coke and Pepsi are \$0.198 (31%) and \$0.209 (35%), respectively. Under dynamic pricing, the equilibrium profit margins of Coke and Pepsi are \$0.153 (24%) and \$0.165 (28%), respectively. This means that profit margins increase by 1.5c (2.3%) and 2.5c (4.2%) when harvesting incentives are introduced, and decrease by 4.5c (6.9%) and 4.3c (7.3%) when investing incentives are additionally introduced, the net effect being that the profit margins are lower than those in the absence of inertia. In other words, the investing incentive dominates the harvesting incentive for the two cola brands, thus yielding equilibrium prices for the both brands that are lower than those in the absence of inertia. These results validate the analytical implications of the normative pricing models of Chintagunta and Rao (1996), Villas-Boas (2004), Dube, Hitsch and Rossi (2009) and Doganoglu (2010).

Next, we compute the amount of foregone profit to each manufacturer that results from not undertaking dynamic pricing and, instead, wrongly employing myopic pricing for its brand, while the competing manufacturer correctly undertakes dynamic pricing for its brand. We find that Coke's (Pepsi's) profit increases by 7.6 % (4.8 %), while Pepsi's (Coke's) profit decreases by 4.7 % (5 %), when Pepsi (Coke) wrongly chooses myopic pricing for its brand. This shows

that substantively meaningful losses in profits accrue to cola brands from not employing dynamically optimal pricing strategies for their brands.

In order to further understand the substantive implications of our estimated structural model of dynamic pricing, we perform a series of counterfactual simulations. Given the estimated structural parameters from our proposed dynamic pricing model, and given a specific simulation scenario, we compute the optimal prices, under different states, S and v , for the manufacturers. For this purpose, we use the NFXP algorithm of Pakes and McGuire (1994). Computational details are provided in Appendix 2.

1.6.1 Counterfactual Simulation 1: Effects of Discount Factors

We compute the steady-state prices, steady-state demands, as well as steady-state single-period profits, for Coke and Pepsi, at various values of discount factors (assumed to be common across the two firms). The purpose of this simulation is to investigate the impact of manufacturers' forward-looking behavior on price competition among brands and, therefore, the resulting impact on their steady-state profits. Lowering the discount factor, and thus assuming that manufacturers are less forward looking, decreases manufacturers' investing incentives, while keeping their harvesting incentives unchanged. This should increase the equilibrium prices of both brands. However, the losses associated with decreased demand, which are partly a function of decreased customer lock-in for the long run, of such increases in equilibrium prices, may more than offset the gains associated with increased prices and, therefore, lead to a net decrease in steady-state profits of the manufacturers. Figure 1.1 presents the steady-state single-period profits of both brands as functions of the discount factors. We observe the following:

- As the discount factor increases from 0 to 0.69, both Coke's and Pepsi's profits steadily increase, with the percentage increase in profits being larger for Pepsi (0.62 %) than for Coke (0.24 %).
- As the discount factor increases from 0.69 to 0.86, Coke's profits steadily decrease (by 0.26 %), while Pepsi's profits continue to steadily increase (by 0.21 %).
- As the discount factor increases from 0.86 to 0.99, both brands' profits steadily decrease (by 1.03 % and 1.47 % for Coke and Pepsi, respectively).

In other words, both sufficiently low discount factors (< 0.69) and sufficiently high discount factors (> 0.86) yield lower profits than intermediate values of discount rates for Coke and Pepsi. In terms of cola category profits, we find that they steadily increase up to a discount rate of 0.81, beyond which they start decreasing.

In order to better elucidate the profit findings in Figure 1.1, we plot the steady-state prices of both brands as functions of discount rates in Figure 1.2. As discussed above, we find that prices of both brands steadily decrease, at an increasing rate, as the discount rate increases. Specifically, Pepsi's equilibrium price decreases from \$0.80 to \$0.76 (5 %), while Coke's decreases from \$0.85 to \$0.80 (5.9 %), as the discount rate increases from 0 to 0.99. The corresponding demands¹³ are found to steadily increase in a convex manner. Figure 1.2 make it clear that the investing incentive, which steadily increases as the discount rate increases, decreases the equilibrium prices of both brands from their myopic levels (corresponding to a discount rate of 0). Interestingly, however, the net effect to each firm of a decreasing profit margin and increasing demand, both of which result from a decreasing price, at steady state

¹³ The steady-state demands are available from the authors upon request.

yields the non-monotonic curve shown in Figure 1.1. Since previous empirical studies have only focused only on a comparison of a dynamic pricing model (which corresponds to a discount factor close to 1) to a myopic pricing model (which discounts to a discount factor of 0), there is no existing empirical wisdom on the impact of different discount factors on firms' profits. Ours is the first study to contribute in this regard.

1.6.2 Counterfactual Simulation 2: Effects of Discount Factor Combinations

We compute the steady-state prices, steady-state demands, as well as steady-state single-period profits, for Coke and Pepsi, at various combinations of values of discount factors (from 0 to 0.99) between Coke and Pepsi. In other words, we allow Coke and Pepsi to have different discount factors (unlike counterfactual simulation 1, which assumes that both manufacturers have identical discount factors). Figure 1.3 presents the steady-state profits of both brands, as well as the cola category as a whole, as functions of various discount factor combinations. We observe the following:

- Each brand's profit is increasing in its own discount factor and decreasing in the competing brand's discount factor.
- Using the highest discount factor (0.99) is a dominant strategy for each firm in the sense of yielding the highest profit regardless of what discount factor its competitor uses.
- Cola category profits are maximized when Pepsi's discount factor is 1 and Coke's discount factor is 0.

This counterfactual simulation suggests that near-maximal foresight (i.e., discount factor of 0.99), which is what we assume about manufacturer rationality in our structural model of

dynamic pricing, is a dominant strategy for both Coke and Pepsi in the sense of yielding the highest profit to each manufacturer regardless of what discount factor its competitor uses.

1.6.3 Counterfactual Simulation 3: Effects of Increasing Inertia

We have discussed that investing incentives to pricing dominate harvesting incentives in our data. However, the relative importance of one incentive compared to the other, in general, would depend on the degree of inertia in demand. In this counterfactual simulation, we study how the relative importance of each incentive varies as the degree of inertia in the market varies from low to high. One way of increasing consumer inertia toward cola brands may be to increase reminder advertising in the category using media such as billboards and television (for example, by using catchy jingles, such as “The Real Thing” for Coke, and the “Pepsi Generation” for Pepsi), which increase “top of mind” recall among the installed bases of each brand toward their favored brands and, therefore, make them repeat purchase the favored brands with greater likelihood.¹⁴ We compute the steady-state prices, steady-state demands, as well as steady-state single-period profits, for Coke and Pepsi, at various values of the inertia parameter for one segment at a time. Figures 1.4 and 1.5 present the steady-state profits of both brands as functions of the inertia parameter for segments 1 and 2, respectively. We observe that the profits of both brands increase as inertia of either segment increases. Specifically, as the inertia parameter of segment 1 (2) increases from 0 to 3.5, the profits of Coke and Pepsi increase by 292 % (88 %) and 341 % (151 %), respectively. As the inertia parameter of segment 1 (2) increases from its existing value of 1.6 (0.9) to 3.5, the profits of Coke and Pepsi increase by 147 % (218 %) and 140 % (227 %), respectively. These are sizeable increases in profits for both brands.

¹⁴ Seetharaman (2004) shows that in-store display advertising, as well as newspaper feature advertising, serve this role by increasing consumer inertia toward brands in the long run.

In order to better elucidate the profit findings in Figures 1.4 and 1.5, we plot the steady-state prices of both brands as functions of the inertia parameter for segments 1 and 2, respectively, in Figures 1.6 and 1.7. We find in both figures that as inertia increases, the price of each brand steadily decreases -- first at an increasing rate, then linearly, and eventually at a decreasing rate -- until it reaches a minimum and then starts increasing. Specifically, in Figure 1.6 (1.7), Coke's price decreases from \$0.83 (\$0.81) to \$0.80 (\$0.78), i.e., 3.6 % (3.7 %), as the inertia parameter of segment 1 (2) increases from 0 to 2 (3.5), and then starts increasing. In the same figure, Pepsi's price decreases from \$0.76 (\$0.76) to \$0.75 (\$0.74), i.e., 1.3 % (2.6 %), as the inertia parameter of segment 1 (2) increases from 0 to 1 (3), and then starts increasing. This implies that the investing incentive dominates the harvesting incentive at low and moderate levels of inertia, while the harvesting incentive dominates the investing incentive at high levels of inertia.

The steady-state demands for both brands that correspond to the brand prices reflected in Figure 1.6 and 1.7 are found to steadily increase as the inertia parameter of the respective segment increases. In order to see how the steady-state demand within each segment behaves, we separately plot the steady-state demand from each segment in Figures 1.8 and 1.9. Interestingly, in Figure 1.8 (1.9), we observe monotonically increasing demand from segment 1 (2), but a non-monotonicity in demand -- increasing with inertia, reaching a maximum, and decreasing thereafter -- from segment 2 (1). The non-monotonicity for segment 2 (1) happens at the value of inertia that corresponds to the non-monotonicity in price that is observed in Figure 1.6 (1.7) for the same segment. In other words, since the inertia parameter for segment 2 (1) is fixed in Figure 1.8 (1.9), increasing the price of a brand decreases demand for the brand, which is not surprising. However, the increase in inertia for segment 1 (2) in Figure 1.8 (1.9) overwhelms the increase in

price of a brand, when it happens, and sustains the increase in demand for the brand from that segment over the entire range of inertia tested in this simulation.

1.7 Conclusions

In this study, we propose and estimate, for the first time in the literature, a structural dynamic pricing model in the presence of inertial demand. For this purpose, we study the cola market, which is characterized by significant inertia in consumers' brand choices over time. We estimate a consumer-level brand choice model, which includes the effects of inertia, using *scanner panel data* on cola brand choices of consumers in a local market over a period of two years. We then estimate a manufacturer-level oligopolistic pricing model using *retail tracking data* on store-level prices of cola brands from the same local market over the same period of two years. Using a two-segment brand choice model, we find that the cola category is characterized by significant inertia in demand, with estimated brand-level switching costs of \$0.30 and \$0.13 for the two consumer segments. Not accounting for such inertia in brand choices leads to seriously mis-estimated sensitivities of cola demand to marketing mix variables.

We find that ignoring the investing incentives in manufacturers' dynamic pricing, as represented in our dynamic pricing model, leads to a spurious overestimation in the estimated profit margins of 29 % and 40 % for Coke and Pepsi, respectively. Ignoring both the investing and harvesting incentives leads to a spurious overestimation in the estimated profit margins of 19 % for both brands. Estimating a mis-specified demand model without inertia and using it as an input for a static pricing model leads to estimated profit margins that are slightly lower than those implied by the static pricing model that simply sets the inertia parameter to zero among the estimated parameters yielded by a demand model with inertia.

The net impact of the harvesting and investing incentives in our data is that the equilibrium prices of both brands are *lower* (by 4.6 % and 3.1 % of costs, for Coke and Pepsi, respectively) than those in the absence of inertia. In other words, the harvesting incentive --

which increases equilibrium prices of Coke and Pepsi by 2.3 % and 4.2 %, respectively -- is dominated by the investing incentive -- which decreases equilibrium prices of Coke and Pepsi by 6.9 % and 7.3 %, respectively -- for cola brands. We find that each brand's profits would decrease by about 5 % if it were to engage in myopic pricing while its competitor engages in dynamic pricing.

A counterfactual simulation reveals that increasing the discount factor from 0 to 1 initially increases, and eventually decreases, the profits of the two brands. Another counterfactual simulation reveals that each brand's profits increase in its own discount factor and decrease in its competitor's discount factor. A third counterfactual simulation reveals that the investing incentive to pricing dominates at low to moderate levels of inertia, while the harvesting incentive dominates at high levels of inertia. However, profits of both brands steadily increase with inertia.

Some caveats are in order. First, we treat prices as exogenous in our demand model, i.e., we do not allow for unobserved demand shocks. We acknowledge that our estimates of marginal costs may, therefore, be over-estimated if such unobserved demand shocks exist (see Che, Sudhir and Seetharaman 2007 for a discussion of this issue). Second, our model does not capture an additional source of dynamics in demand, i.e., due to consumer stockpiling behavior, which has implications for dynamic pricing. In the cola category, however, stockpiling is not pervasive as revealed in our data. Households typically buy their preferred quantity of cola on purchase occasions. Therefore, ignoring the effects of consumer stockpiling may not be a critical omission in our case. That said, while extending our model to product categories where consumer stockpiling is, in fact, significant, explicitly modeling stockpiling behavior, as well as its implications for dynamic pricing, would be necessary. Third, we ignore the strategic role of the

retailer in the analysis. We treat the retailer as a passive intermediary in the distribution channel. We do this mainly for computational convenience since introducing the dynamic pricing incentives of the retailer would lead to non-trivial modeling extensions. However, we still obtain interesting substantive implications from comparing dynamic, myopic, and static pricing incentives of manufacturers using our framework. Extending our model to additionally incorporate the strategic role of the retailer is an important area for future research.

We believe that there are some additional research extensions that would be interesting to pursue. First, investigating the demand conditions under which periodic price promotions of competing brands emerge as a natural by-product of the competitive dynamic equilibrium in the presence of inertia would be interesting (see, for example, Freimer and Horsky (2008), for an interesting analytical model of price promotions in the presence of inertia). Second, extending the analysis to the case of variety seeking (the opposite of inertia) would be useful to understand the dynamic pricing implications of variety seeking markets (see, for example, Seetharaman and Che (2009)). Last, but not least, understanding how to increase inertia in a market to favor one brand over another would be useful not only in its own research right, but also from the standpoint of informing brand managers on how to better leverage inertial demand for more pricing power in the market.

1.8 Technical Appendices

1.8.1 Appendix 1: Forward Simulation:

The objective of this simulation exercise is to calculate the continuation values

$EV_j(s)$, $j = 1, 2, \dots, J$ in the Bellman equations of each manufacturer for a given cost structure (c_j, σ_j), and policy function parameters (β_j) in the numerical search routine. We simulate

numerous paths. For each simulated path, we first choose (s_0, ν_0) from the state space. We then run the following simulation routine:

1. Given (s_0, ν_0) and the assumed parametric policy function calculate $p_0(s_0, \nu_0)$. Then, calculate demand $D_0(s_0, p_0)$
2. Given $p_0(s_0, \nu_0)$, and $D_0(s_0, p_0)$, calculate $\pi_0^j = (p_{0j} - c_j - \nu_j)D_{0j}$. Then calculate the installed customer base in the next period $s_1(s_0, p_0)$.
3. Given s_1 , draw ν_1 . Given (s_1, ν_1) , repeat steps 1 and 2.
4. Repeat step 3 for T times until $\beta^T \approx 0$.

Taking discounted sum of profits calculated for each of the T periods, and averaging over all simulation paths gives us the set of approximated values for each manufacturer $V_j(s_0, \nu_0)$. We then regress these values on (s_0, ν_0) to get an approximated value function for any arbitrary state variables.

1.8.2 Appendix 2: Multi-Agent NFXP Algorithms for the Counterfactual Studies:

The objective of this routine is to find the dynamic pricing equilibrium of the manufacturer pricing game numerically. Here is the algorithm:

1. Start with p_1^0, p_2^0
 - 1.1. Given p_2^0 , get p_1^1 by running the subroutine 2.2.
 - 1.2. Given p_1^1 , get p_2^1 by running the subroutine 3.4
 - 1.3. Repeat 1.1-1.2 until $\|p^n - p^{n-1}\| \approx 0$.
 - 1.4. Set $p^* = p^n$

Appendix 2.1: Subroutine Coke's Optimality

The objective of this subroutine is to find the best response of Coke p_1^* to a given set of actions of Pepsi p_2 , under a given continuation value in Coke's Bellman equation $EV_1(s)$. In other words, the objective is given by

$$p_1 = \arg \max \{ (p_1 - c_1 - v_1)D_1 + \beta E_{v_1} V_1(s' | s, p) \}$$

where D_1 is the demand for Coke. In order to find optimal p_1^*

1. Start with p_1^0 . Given p_1^0 calculate the following:

$$\frac{\partial EV_1(s, v_1)}{\partial p_1} = D_1 + (p_1 - c_1 - v_1)D_{11} + \beta EV_{11}(s')$$

where $D_{11} = \partial D_1 / \partial p_1$, and $EV_{11} = (\partial EV_1(s') / \partial s')(\partial s' / \partial p_1)$

By rearranging, we can get p_1^1 as follows:

$$p_1^1 = c_1 + v_1 - [D_1 + \beta EV_{11}(s')]D_{11}^{-1}$$

2. Given p_1^1 , repeat step 1, to get p_1^2
3. Repeat step 2 to update p_1 until an iteration n such that $\|p_1^n - p_1^{n-1}\| \approx 0$
4. Set $p_1^* = p_1^n$

Appendix 2.2: Subroutine Coke's Dynamic Response

The objective of this subroutine is to find the dynamic best response of Coke to the set of actions of Pepsi: p_2 . Here is how it goes:

1. Start with $EV_1^0(s) = 0$: the continuation value in Coke's Bellman equation is zero.
 - a. Get p_1^{0*} under $EV_1^0(s) = 0$ by using the subroutine 2.1. Given p_1^{0*}, p_2 calculate the following Bellman equation:
$$V_1^1(s, \nu) = (p_1^{0*} - c_1 - \nu_1)D_1 + \beta E_{\nu'} V_1(s' | s, p_1^{0*}, p_2)$$
 - b. Given $V_1^1(s, \nu)$, calculate $EV_1^1(s)$ by averaging over ν . Given $EV_1^1(s)$ get p_1^{1*} by using the subroutine 2.1. Calculate the Bellman equation in (a) under p_1^{1*}, p_2 . Calculate the updated continuation value $EV_1^2(s)$.
 - c. Repeat (b) until an iteration n such that $\|p_1^{n*} - p_1^{n-1*}\| \approx 0$
 - d. Set $p_1^* = p_1^{n*}$

Appendix 2.3: Subroutine Pepsi's Optimality

The objective of this subroutine is to find the best response of Pepsi p_2^* to a given set of actions of Coke p_1 , under a given continuation value in Pepsi's Bellman equation $EV_2(s)$. In other words, the objective is given by

$$p_2 = \arg \max \{ (p_2 - c_2 - \nu_2)D_2 + \beta E_{\nu'} V_2(s' | s, p) \}$$

where D_2 is the demand for Pepsi. In order to find optimal p_2^*

1. Start with p_2^0 . Given p_2^0 calculate the following:

$$\frac{\partial V_2(s, \nu)}{\partial p_2} = D_2 + (p_2 - c_2 - \nu_2)D_{22} + \beta EV_{22}(s')$$

where $D_{22} = \partial D_2 / \partial p_2$, and $EV_{22} = (\partial EV_2(s') / \partial s')(\partial s' / \partial p_2)$

By rearranging, we can get p_2^1 as follows:

$$p_2^1 = c_2 + \nu_2 - [D_2 + \beta EV_{22}(s')]D_{22}^{-1}$$

2. Given p_2^1 , repeat step 1, to get p_2^2
3. Repeat step 2 to update p_2 until an iteration n such that $\|p_2^n - p_2^{n-1}\| \approx 0$

4. Set $p_2^* = p_2^n$

Appendix 2.4: Subroutine Pepsi's Dynamic Response

The objective of this subroutine is to find the dynamic best response of Pepsi to the set of actions of Coke: p_1 . Here is how it goes:

1. Start with $EV_2^0(s) = 0$: the continuation value in Pepsi's Bellman equation is zero.
 - a. Get p_2^{0*} under $EV_2^0(s) = 0$ by using the subroutine 2.3. Given p_1, p_2^{0*} calculate the following Bellman equation:
$$V_2^1(s, \nu) = (p_2^{0*} - c_2 - \nu_2)D_2 + \beta E_\nu V_2(s' | s, p_1, p_2^{0*})$$
 - b. Given $V_2^1(s, \nu)$, calculate $V_2^1(s)$ by averaging $V_2^1(s, \nu)$ over ν . Given $V_2^1(s, \nu)$ get p_2^{1*} by using the subroutine 2.3. Calculate the Bellman equation in (a) under p_1, p_2^{1*} . Calculate the updated continuation value $EV_2^2(s)$.
 - c. Repeat (b) until an iteration n such that $\|p_2^{n*} - p_2^{n-1*}\| \approx 0$
 - d. Set $p_2^* = p_2^{n*}$

1.8.3 Appendix 3: Stockpiling Behavior of Consumers

I checked 1) the correlation between the quantities purchased and prices paid 2) the correlation between the interpurchase times and prices paid. I found that there is no strong correlation for either scenario.

i) Correlation between Quantity (Q_t) and Price (P_t)

$Cor(Q_{th}/Q_h, P_t) = -0.078$, where

Q_{th} = quantity purchased by household h at time t

Q_h = median quantity for household h over time t

ii) Correlation between Interpurchase time (IP_t) and Price (P_t)

$$Cor\left(\frac{IP_{th} - \mu_{IP_h}}{\sigma_{IP_h}}, \frac{P_{th} - \mu_{P_h}}{\sigma_{P_h}}\right) = 0.0006$$

These two statistics show that we have very low reason to believe that the stockpiling behavior is significant in the data.

Table 1.1: Descriptive Statistics on Cola Dataset (June 1991-June 1993)¹⁵

Number of Households = 356
 Number of Shopping Trips = 32942
 Number of Purchases = 5784

Brand	Price (\$ / unit)	Display	Feature	Market Share
Coke	\$0.8050 (\$0.0680)	0.1458 (0.0953)	0.2535 (0.1249)	0.3027 (0.1038)
Pepsi	\$0.7500 (\$0.0574)	0.2236 (0.1818)	0.3314 (0.2088)	0.4567 (0.1173)
Royal Crown	\$0.8051 (\$0.0747)	0.0943 (0.0788)	0.1067 (0.0883)	0.1721 (0.0906)
Private Label	\$0.5311 (\$0.0740)	0.1044 (0.0780)	0.0641 (0.0849)	0.0685 (0.0572)

¹⁵ Standard Deviations are reported within parentheses.

Table 1.2: Estimation Results – Inertial Demand Model (2-Support Heterogeneity)¹⁶

LL = -13716.32, BIC = 27624.15

	Segment 1	Segment 2
α_{Coke}	0.950 (0.183)	-0.019 (0.177)
α_{Pepsi}	1.028 (0.181)	0.136 (0.181)
α_{PL}	-2.144 (0.194)	-1.677 (0.138)
$\alpha_{RoyalCrown}$	0.516 (0.167)	-0.481 (0.166)
β_{Price}	-5.233 (0.232)	-6.727 (0.239)
$\beta_{Display}$	1.113 (0.078)	1.454 (0.071)
$\beta_{Feature}$	0.228 (0.078)	0.320 (0.078)
λ_{SD}	1.560 (0.050)	0.858 (0.048)
Size	29 %	71 %

Table 1.3: Estimation Results –Demand Model without Inertia (2-Support Heterogeneity)¹⁷

LL = -14460.57, BIC = 29090.12

	Segment 1	Segment 2
α_{Coke}	2.386 (0.164)	0.072 (0.192)
α_{Pepsi}	2.608 (0.160)	0.259 (0.194)
α_{PL}	-1.826 (0.171)	-1.469 (0.144)
$\alpha_{RoyalCrown}$	1.577 (0.152)	-0.427 (0.179)
β_{Price}	-6.223 (0.215)	-6.544 (0.258)
$\beta_{Display}$	1.086 (0.070)	1.449 (0.079)
$\beta_{Feature}$	0.195 (0.072)	0.345 (0.082)
Size	35 %	65 %

¹⁶ Standard errors are reported within parentheses in Tables 1.3, 1.4 and 1.5. The standard errors in Table 1.4 are bootstrapped standard errors.

¹⁷ Standard errors are reported within parentheses in Tables 1.3, 1.4 and 1.5. The standard errors in Table 1.4 are bootstrapped standard errors.

Table 1.4: Estimation Results – Manufacturer Pricing Model

	Dynamic	Myopic	Static1	Static2
C_{Coke}	\$0.650 (\$0.019)	\$0.605 (\$0.017)	\$0.621 (\$0.013)	\$0.635 (\$0.012)
C_{Pepsi}	\$0.593 (\$0.020)	\$0.531 (\$0.019)	\$0.563 (\$0.013)	\$0.569 (\$0.014)
V_{Coke}	\$0.068 (\$0.015)	\$0.072 (\$0.007)	\$0.068 (\$0.007)	\$0.071 (\$0.007)
V_{Pepsi}	\$0.060 (\$0.013)	\$0.064 (\$0.006)	\$0.059 (\$0.005)	\$0.064 (\$0.005)

Table 1.5: Equilibrium Prices and Profits

	Dynamic	Myopic	Static
P_{Coke}	\$0.803 (0.019)	\$0.848 (0.020)	\$0.833 (0.020)
P_{Pepsi}	\$0.758 (0.020)	\$0.802 (0.024)	\$0.777 (0.023)
Margin _{Coke}	\$0.153 (0.007)	\$0.198 (0.012)	\$0.183 (0.008)
Margin _{Pepsi}	\$0.165 (0.008)	\$0.209 (0.015)	\$0.184 (0.009)

Figure 1.1: Steady-State Profits as a Function of Discount Factor

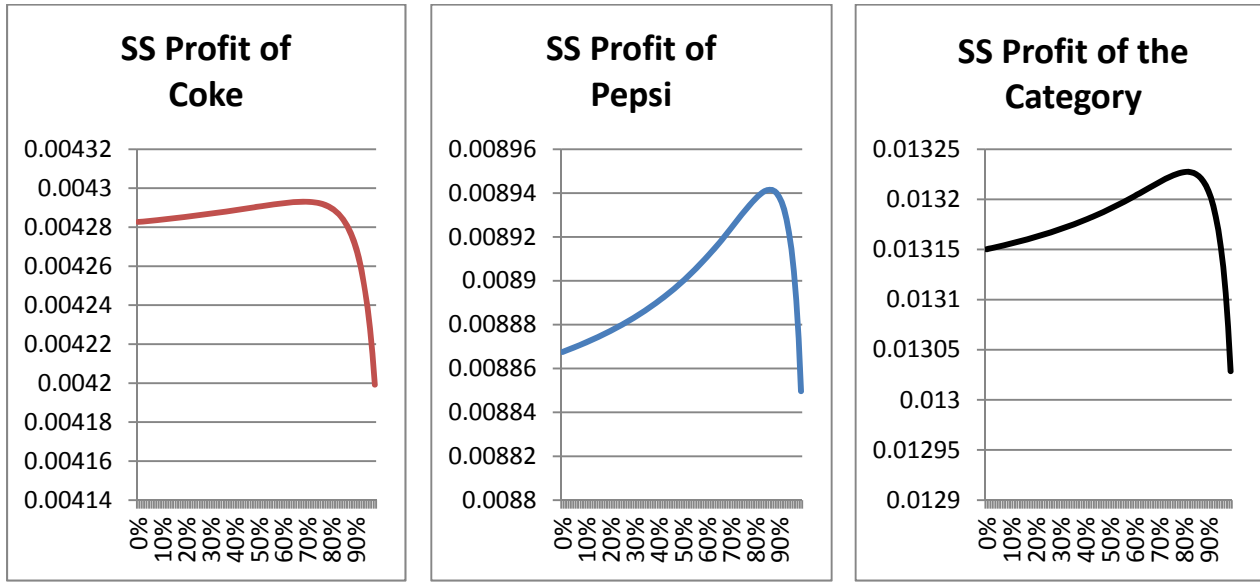


Figure 1.2: Steady-State Prices as a Function of Discount Factor

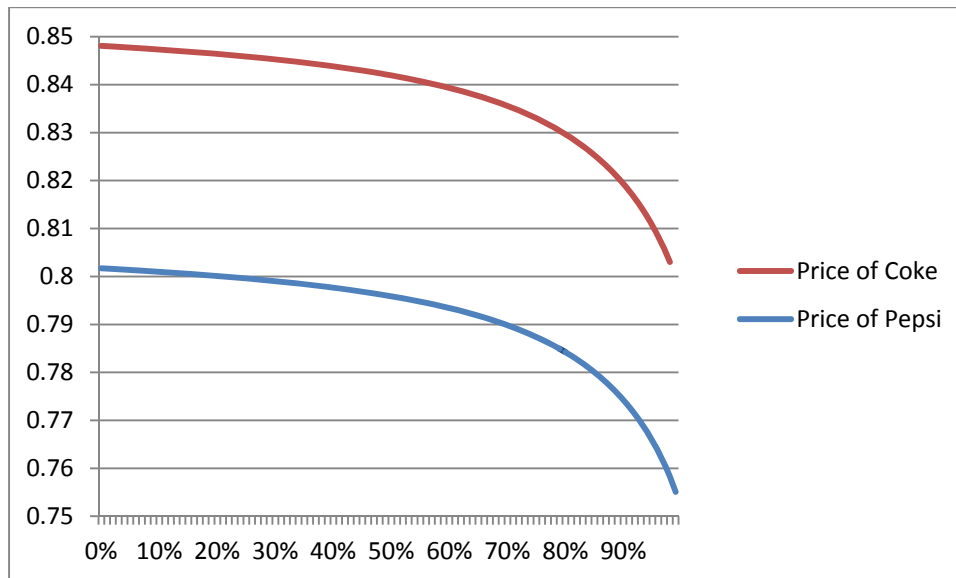
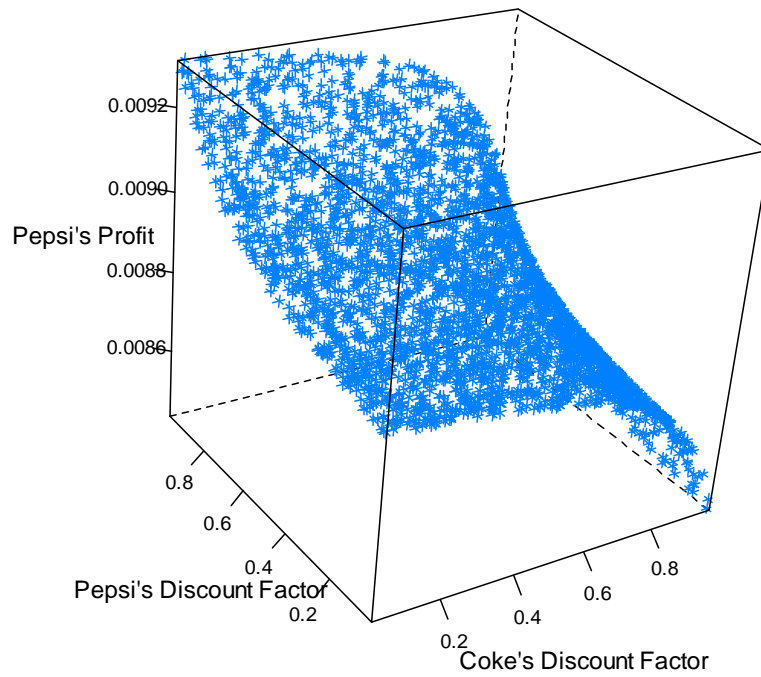
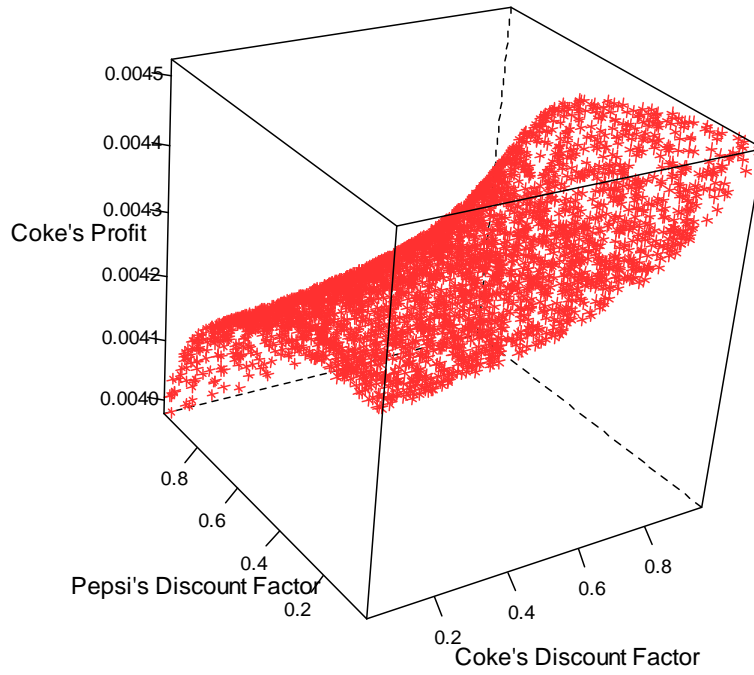


Figure 1.3: Steady-State Profits versus Discount Factor Combinations



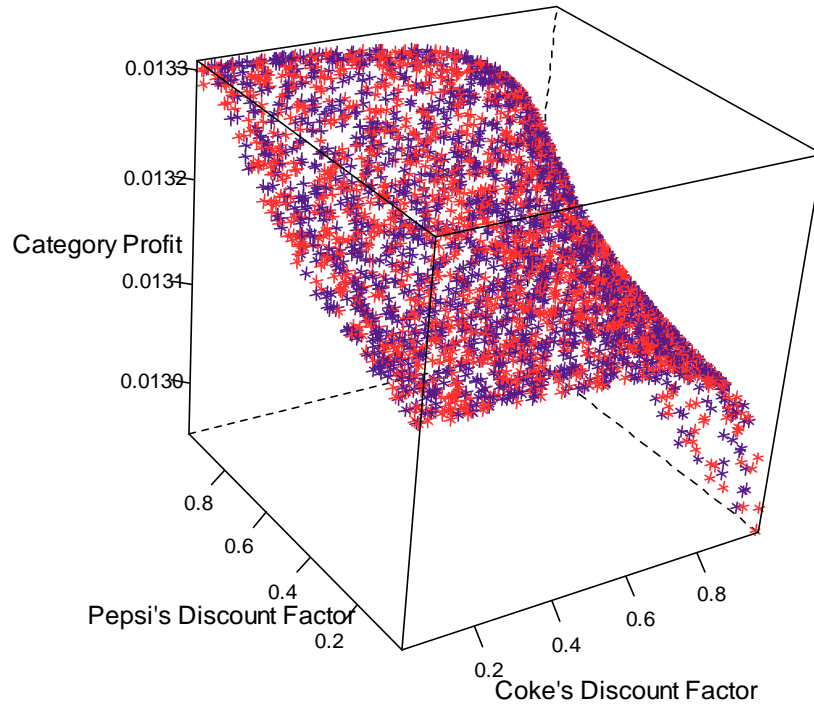


Figure 1.4: Steady-State Profits as a Function of Segment 1 Inertia

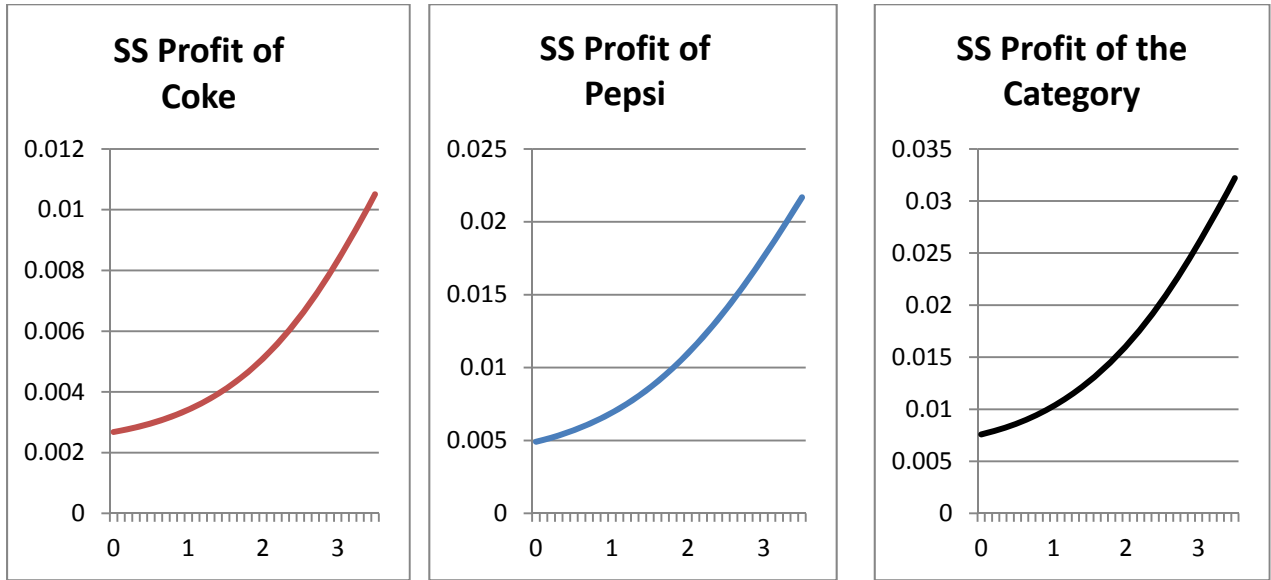


Figure 1.5: Steady-State Profits as a Function of Segment 2 Inertia

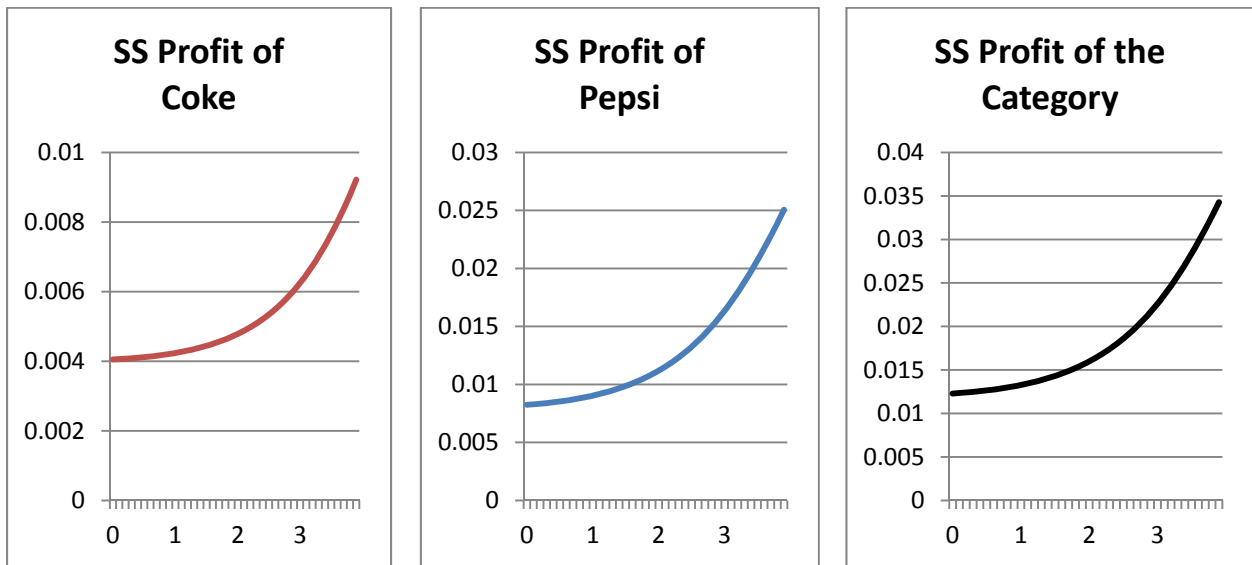


Figure 1.6: Steady-State Prices as a Function of Segment 1 Inertia

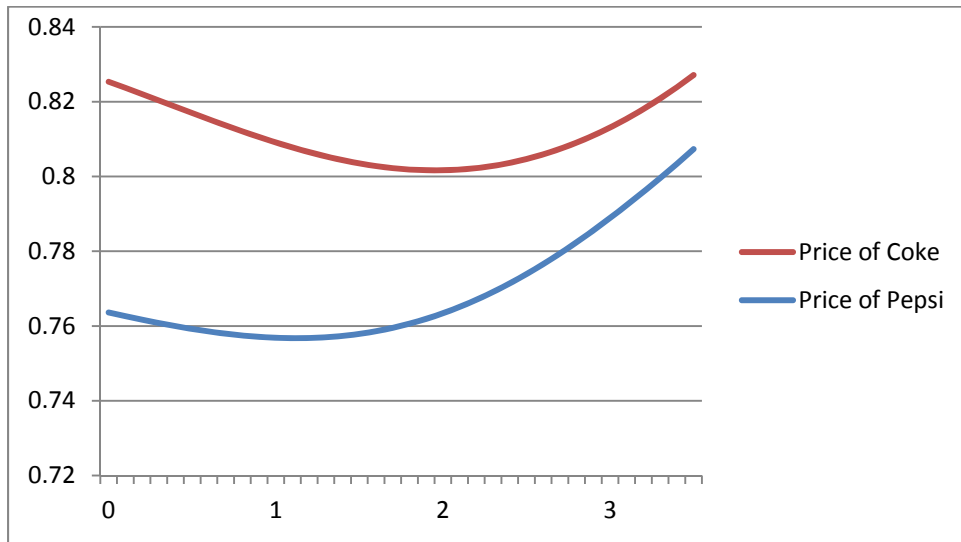


Figure 1.7: Steady-State Prices as a Function of Segment 2 Inertia

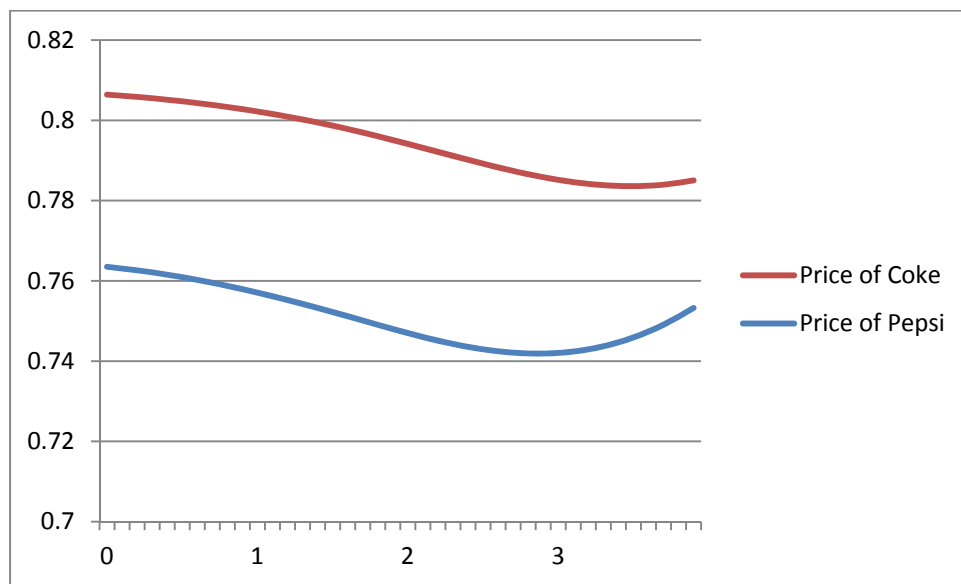


Figure 1.8: Steady-State Demands as a Function of Segment 1 Inertia

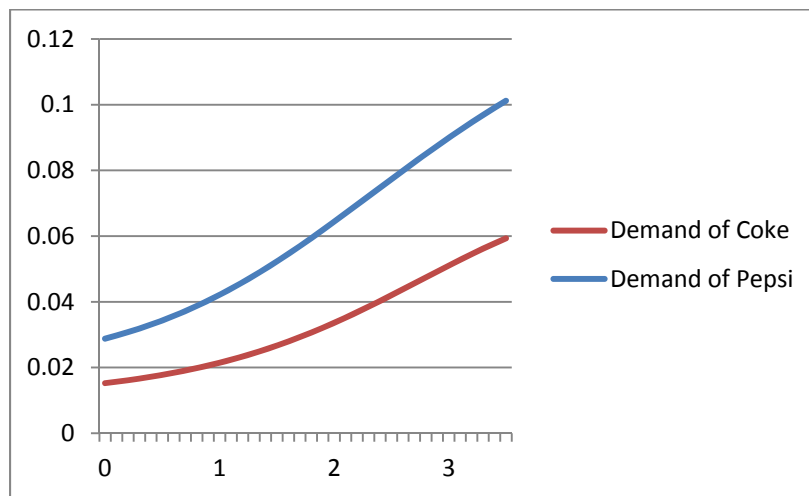
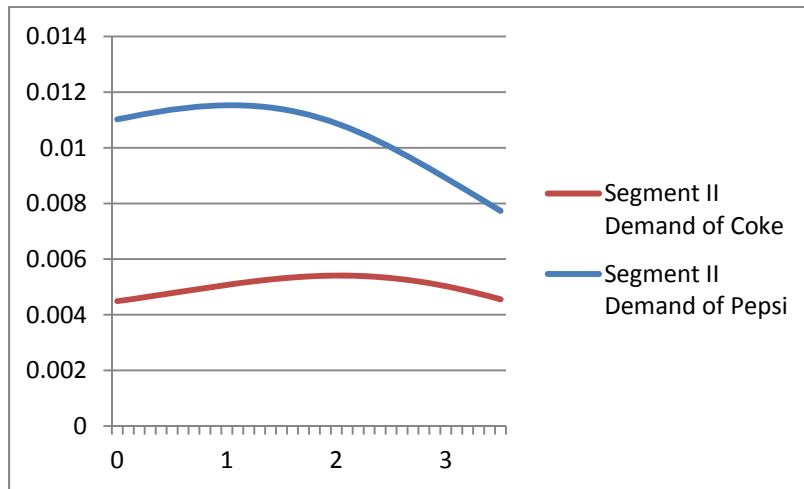
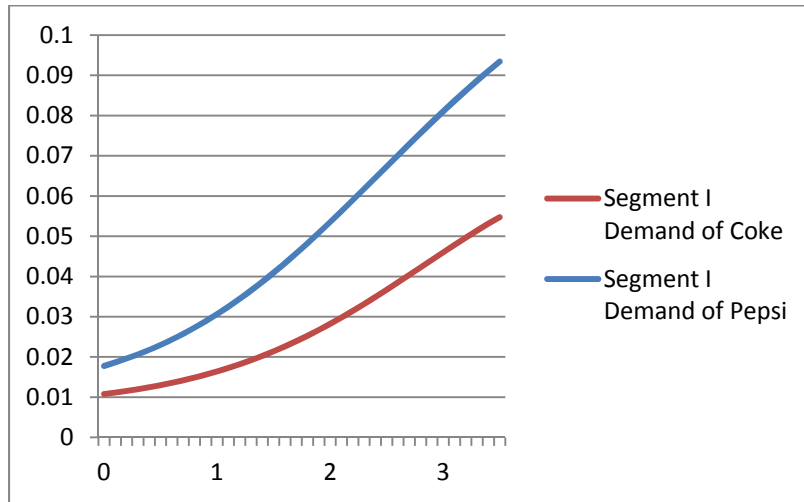
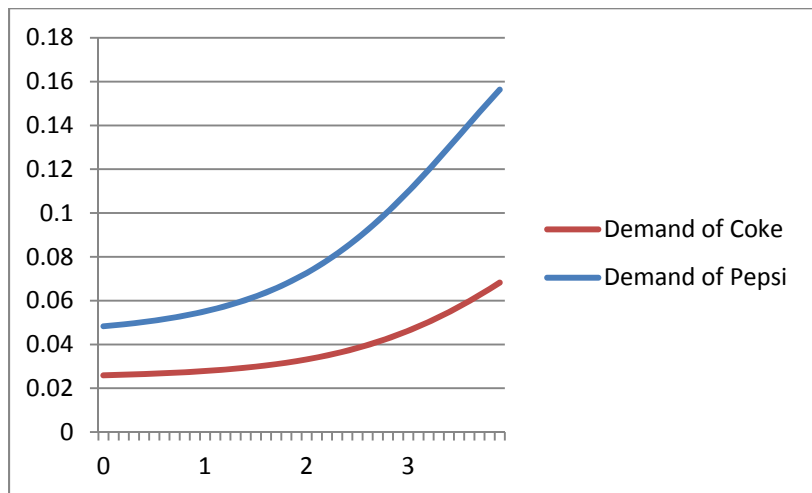
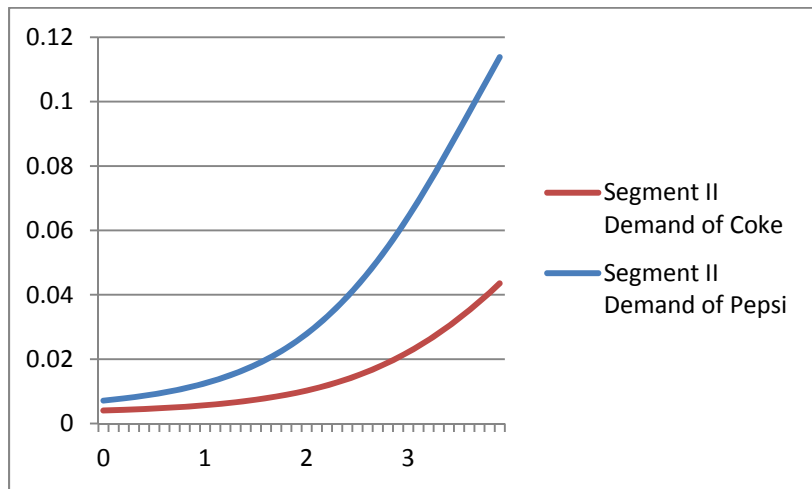
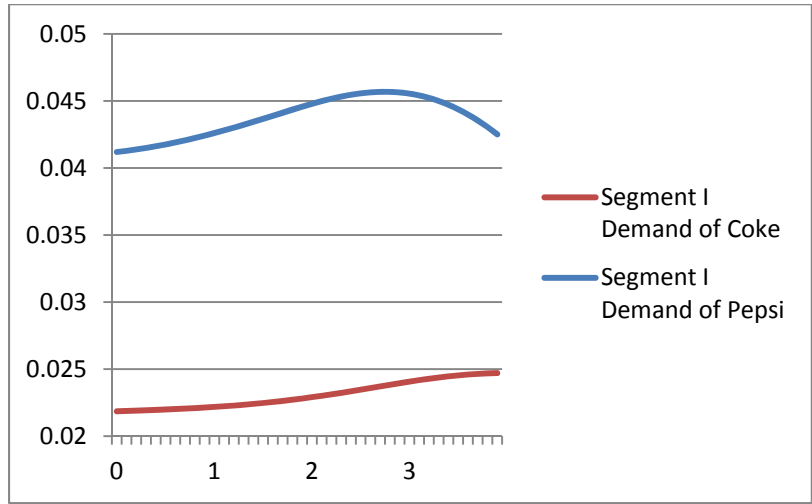


Figure 1.9: Steady-State Demands as a Function Segment 2 Inertia



2 Implications of Inertial Demand for Prices in the Distribution Channel: A Structural Econometric Approach

2.1 Introduction

Consumer product manufacturers, such as Coke and Pepsi, typically sell their brands through common, independent retailers, such as Kroger. Recent research in the structural econometric tradition has dealt with the empirical estimation, using real-world scanner data, of the nature of strategic price interactions in distribution channels, both *horizontally* among manufacturers, as well as *vertically* between manufacturers and the common retailer through which they sell (see, for example, Kadiyali, Chintagunta and Vilcassim (2000), Sudhir (2001), Villas-Boas and Zhao (2005), Villas-Boas (2007), Che, Sudhir and Seetharaman (2007), Draganska, Klapper and Villas-Boas (2010) etc.).¹⁸ Such structural econometric models of pricing in the distribution channel are of great normative value to product manufacturers and retailers from the standpoint of evaluating and setting optimal pricing policies for their brands (Bronnenberg, Rossi and Vilcassim (2005)).

It is well documented in the marketing literature that consumer product markets are commonly characterized by *inertia* in consumers' brand choices over time (see, for example, Seetharaman (2004)).¹⁹ Inertia refers to the phenomenon of consumers often repeat-purchasing the same brand of cola on successive purchase occasions. Such inertial, or habitual, brand choice behavior of consumers, in turn, leads to the aggregate (e.g., market-level) demand for a brand being positively correlated over time. In other words, if demand for a brand is high (low) on a

¹⁸ The reader is referred to Villas-Boas and Zhao (2005) for an insightful discussion on why it is necessary to jointly consider the strategic behavior of both manufacturers and the retailer while econometrically analyzing retail prices.

¹⁹ Economists usually refer to *inertia* using the term *switching costs*.

given week, it is likely to remain high (low) in ensuing weeks on account of consumer inertia. A pricing implication of such inertia in demand, for example, is that reducing the retail price of Coke in the current week will increase the demand for Coke not only in the current week but also in the subsequent weeks when the price reduction on Coke has been retracted (as long as all other competing cola brands' retail prices remain unchanged).

The presence of inertial demand implies that the retailer, while choosing Coke's retail price in a given week, would face a trade-off between charging a low price on Coke to attract customers and locking them in to Coke, versus charging a high price to extract higher profits from Coke's already locked-in customers. The retailer faces a similar trade-off while choosing Pepsi's retail price in a given week. In sum, therefore, the retailer faces an interesting trade-off in pricing the cola brand portfolio, for example, in terms of deciding whether to price both Coke and Pepsi low, versus pricing only Coke (Pepsi) low, versus pricing neither brand low, in a given week. In order to correctly resolve this trade-off when setting retail prices for cola brands, taking the manufacturers' wholesale prices as given, the retailer must know the extent of inertia in consumers' brand choices in the cola market, and whether the pricing implications of such inertia are similar or not among the various brands.

Coca Cola Co. (PepsiCo) must also account for the downstream retailer's above-mentioned pricing strategy, as well as its competitor PepsiCo's (Coca Cola Co.'s) pricing strategy, both of which, in turn, depend on the degree of inertial demand enjoyed by the cola brands among consumers, while choosing wholesale prices for their Coke (Pepsi) brand. For example, suppose Coca Cola Co. knows that the retailer has an incentive to price Coke high in the current period, in order to harvest the existing demand of past consumers of Coke. In that case, the manufacturer could then charge higher wholesale prices for Coke to the retailer than

otherwise. Conversely, suppose the brand manufacturer knows that the retailer has an incentive to price Coke low in the current period, in order to invest in increasing the future demand for the Coke. In this case, the manufacturer must then charge appropriately lower wholesale prices for Coke to the retailer than otherwise in order to induce the retailer to offer adequately lower retail prices to the market.

To summarize, therefore, econometrically analyzing the pricing implications of inertial demand in the context of a distribution channel involves a careful accounting and resolution of the incentives of competing manufacturers in setting wholesale prices, as well as the incentives of the common retailer through whom they sell in determining retail prices, for the different brands in the category. *The primary research contribution of our paper rests in our proposal and estimation of a structural econometric model of dynamic pricing decisions of manufacturers and a common retailer in the presence of inertia in consumers' brand choices.* Such a model will be of obvious value to both brand managers and store managers, given the glut of consumer-level data and analytical tools that are fast permeating the retailing sphere, in guiding strategic pricing efforts for their brands.

We estimate a consumer-level brand choice model, which includes the effects of inertia, using *scanner panel data* on cola brand choices of consumers in a local market over a period of two years. We then estimate a structural econometric pricing model, that accounts for the pricing interactions, both among manufacturers, as well as between each manufacturer and the retailer, using *retail tracking data* on store-level prices of cola brands from the same local market over the same period of two years. Using a two-segment brand choice model, we find that the cola category is characterized by significant inertia in demand, with estimated brand-level switching costs of \$0.30 and \$0.13 for the two consumer segments.

The net impact of the harvesting and investing incentives for cola manufacturers in our data is that the equilibrium wholesale prices of both brands are *lower* (by 11.9 % and 7.1 % of costs, for Coke and Pepsi, respectively) than those in the absence of inertia. In other words, the harvesting incentive -- which increases equilibrium wholesale prices of Coke and Pepsi by 5.2 % and 11.3 %, respectively -- is dominated by the investing incentive -- which decreases equilibrium wholesale prices of Coke and Pepsi by 17.1 % and 18.4 %, respectively -- for cola brands. For the retailer, however, while the harvesting incentive increases the retailer's profit margin by 1.9c and 2.5c, the investing incentive has no impact on retail profit margin. In other words, while the retailer exploits the benefit of the harvesting incentive, by appropriately increasing his retail profit margin, almost equally with the manufacturers, the cost of investing is borne entirely by the manufacturers. In other words, the retailer effectively free rides on the manufacturers' efforts by taking a lion's share of the additional profits that accrue to the channel from the existence of inertial demand. In terms of the net effect of the harvesting and investing incentives on distribution channel profits, we uncover a 3c lowered channel profit margin for Coke, but no change in the channel profit margin for Pepsi.

Using the estimates of our structural econometric model, we study the impact of inertial demand on the estimated profitability of the retailer and each manufacturer using two counterfactual simulations. In the first counterfactual simulation, we study the impact of increasing inertia on each channel member's profits and investigate which player in the distribution channel -- manufacturer or retailer -- is in a better position to leverage the benefits of inertial demand in terms of gaining disproportionately more from, say, increasing levels of inertia in the market. We find that all channel members gain from increasing levels of inertia, with the retailer gaining disproportionately more than the manufacturers. The investing incentive

becomes more important for manufacturers as the level of inertia in either consumer segment increases, thus leading to lower wholesale profit margins. However, as far as the retailer is concerned, an interesting asymmetry emerges. As the level of inertia in the less inertial segment increases, the investing incentive becomes more important to the retailer, thus leading to lower retail profit margins, although at a slower rate than for the manufacturers. However, as the level of inertia in the more inertial segment increases, the retailer not only does not bear the costs of the investing incentive (while the manufacturers do), but also ends up free-riding on the manufacturers' efforts by steadily increasing his retail profit margins on both brands. This simulation suggests that the retailer is in a more leveraged position of strength when it comes to exploiting the increase in inertial demand for cola brands in either consumer segment.

In the second counterfactual simulation, we study the benefits of behavioral price discrimination, using price-off coupons that are customized across behavioral segments of consumers, for the retailer and the manufacturers. We find that the retailer can improve retail profit by 4 % by dropping customized coupons to customers belonging to the more price-sensitive / less inertial segment. Interestingly, we find that the retailer can improve retail profit by an additional 7 % by selling its customer database to both cola manufacturers and letting them drop customized coupons for their brands to customers belonging to segment 2, as opposed to dropping the customized coupons itself. In other words, facilitating manufacturer couponing is a more profitable strategy to the retailer than undertaking store couponing itself. Interestingly, this leads to both manufacturers being slightly worse off, in terms of reduced wholesale profits, when compared to the case of no price discrimination. In other words, the retailer not only entirely benefits at the expense of manufacturers, but also induces the manufacturers to invest the necessary effort to generate the additional channel profits.

2.2 Literature Review

There are two seminal game-theoretic studies, namely Beggs and Klemperer (1992) and Wernerfelt (1991), that centrally motivate the importance of our econometric research from the standpoint of pricing strategies of brand manufacturers. We discuss these two studies first, and later studies on the same issue next.

Beggs and Klemperer (1992) derive the normative pricing implications of inertial demand in a differentiated duopoly using an infinite period game-theoretic framework, where new customers arrive and a fraction of old consumers leave in each period. Furthermore, in each period, old (locked-in) customers and new (uncommitted) customers are intermingled and the two firms cannot discriminate between these groups of customers. The authors study whether the firms' temptation to exploit their current customer bases would lead to higher prices (*harvesting* incentive), or whether the firms' desire to attract new customers would lead to lower prices (*investing* incentive), than in the case of no inertia. The authors show that under a wide range of parametric assumptions, both firms – each with an installed base of existing customers – face demand functions that are relatively price inelastic compared to their counterparts in an otherwise identical mature market without inertia. This decreased price elasticity reduces the price rivalry among the firms, leading to higher prices and profits for both firms. The authors show that inertial demand could lead to vigorous price competition in the early growth stages of a market, as competing firms aggressively try to build market shares for their brands. When the modeling framework allows for rational (i.e., “forward-looking”) consumers, the prices of the two firms are shown to become less competitive because consumers who realize that firms with higher market shares will charge higher prices in the future are less price elastic than naïve consumers. The authors find that price rise as (1) firms discount the future more, (2) consumers

discount the future less, (3) turnover of consumers decreases, and (4) the rate of growth of the market decreases.

In contrast to the discrete-time, game-theoretic framework adopted by Beggs and Klemperer (1992), Wernerfelt (1991) adopts a continuous-time, game-theoretic framework to study price competition between firms in inertial markets. Consistent with the findings in Beggs and Klemperer (1992), Wernerfelt (1991) also derives higher equilibrium prices for firms, as well as a positive effect of the extent of firms' future discounting behavior on equilibrium prices, in inertial markets. This shows that the equilibrium pricing results are robust to whether the game-theoretic pricing models are solved in discrete or continuous time.

Unlike Beggs and Klemperer (1992) and Wernerfelt (1991), who show that the harvesting incentive outweighs the investing incentive for manufacturers under a wide range of parametric assumptions, Chintagunta and Rao (1996) and Dube, Hitsch and Rossi (2009) find the opposite to be the case under some parametric assumptions that are based on actual demand estimates. They show that myopic pricing strategies of firms that fail to recognize the long-run impact of their current prices lead to prices that are higher than those implied by dynamic pricing strategies. Doganoglu (2010) obtains the same result when the degree of inertia in demand in his model is assumed to be sufficiently low. Villas-Boas (2004) also derives the same result for the case where inertial demand endogenously arises out of consumers learning about how well different brands fit their preferences, and when the distribution of consumer valuations for each product is negatively skewed. In a recent study, Cosguner, Chan and Seetharaman (2012) obtain the same result by actually estimating an econometric model of oligopolistic manufacturer pricing using retail price data.

All of the models of dynamic pricing discussed above ignore the strategic role of the retailer in the distribution channel. In other words, the pricing implications of inertial demand are derived for manufacturer pricing, tacitly assuming that manufacturers sell directly to end consumers. Two recent studies look at the consequences of inertial demand for retailers' pricing decisions, namely, Che, Sudhir and Seetharaman (2007) and Dube, Hitsch, Rossi and Vitorino (2009). However, Dube et al. (2009) derive optimal retailer prices, ignoring the role of manufacturers and, therefore, treating the retailer's costs as exogenously specified. Che et al. (2007), on the other hand, simultaneously account for the strategic role of competing manufacturers in setting wholesale prices, while deriving optimal retail prices in the distribution channel. Furthermore, Che et al. (2009) take an econometric, as opposed to a purely game-theoretic, approach in explaining retail pricing decisions of retailers. In this sense, the Che et al. (2007) study is closely related to this research. However, given the computational challenges associated with the estimation of a structural econometric model of pricing in the distribution channel (as will be explained in the next paragraph), Che et al. (2007) formulate their pricing model for a finite number of decision periods only (as opposed to infinite periods). Our study relaxes this restrictive assumption and derives the appropriate pricing model for the distribution channel under the general case of infinite period decision-making of manufacturers (as in the game-theoretic literature, see, for example, Beggs and Klemperer (1992) and Wernerfelt (1991)), as well as the retailer. In doing this, we are able to understand the tension between the harvesting and investing incentives of manufacturers and the retailer in driving the observed retail prices of brands in our data. More generally, our approach can be used by manufacturers and retailers in order to correctly assess the long-run consequences of alternative pricing strategies of brands, something that cannot be satisfactorily accomplished using the Che et al. (2007) approach.²⁰

²⁰ Che et al. (2007) represent a pioneering effort in the estimation of dynamic pricing decisions of manufacturers and

Estimable econometric models of dynamic pricing in the distribution channel in the presence of inertial demand require both (1) the solution of discrete-time, stochastic dynamic optimization problems for each manufacturer and retailer, where the manufacturer (retailer) chooses from a continuum of possible wholesale (retail) prices, and (2) the fixed point to the game-theoretic problem of multiple firms (manufacturers and retailer) employing their best pricing responses to each other's pricing choices, to be accommodated in the estimation. Such models, referred to as structural models of dynamic pricing in the distribution channel in the presence of inertial demand, therefore, present significant computational challenges. An additional estimation challenge arises when some firm actions (such as wholesale prices, as in our case) are unobserved by the researcher. In fact, as we will discuss in detail later, this difficulty renders recently developed econometric techniques in the econometrics literature – Pakes and McGuire (2001), Bajari, Benkard and Levin (2007) etc. – inapplicable to our context. We propose a fully dynamic pricing model for the distribution channel, as well as a new estimation method to recover its parameters when some of the agents' actions are unobserved. We apply our structural econometric model of dynamic pricing in the distribution channel to the cola market.

The rest of the paper is organized as follows. In the next section, we present our structural econometric model of inertial demand, as well as the associated estimation procedure. In the third section, we present our structural econometric model of dynamic pricing in the distribution channel in the presence of inertial demand, as well as the associated estimation procedure. Section 4 presents the estimation results from applying our proposed structural econometric models of inertial demand and dynamic distribution channel pricing on scanner panel data from

the retailer in the presence of inertial demand. Our effort represents a logical next step given the computational advances of recent years.

the cola market. In Section 5, we discuss the managerial implications of our estimation results based on some counterfactual simulations, one of which pertains to behavioral price discrimination. Section 6 concludes with caveats and directions for future research.

2.3 Structural Econometric Model of Inertial Demand

To develop a structural econometric model of brand choice with the no-purchase option for scanner panel data in the cola category, we recognize that the typical household h ($h = 1, 2, \dots, H$), which is observed over $t = 1, 2, \dots, T_h$ shopping trips, either buys or does not buy one of J cola brands. On any given shopping trip, we observe an outcome variable y_{ht} that takes the value j ($j = 0, 1, 2, \dots, J$). When $y_{ht} = 0$ it means that the household does not purchase in the cola category during shopping trip t . Further, during each shopping trip of a household, we observe the price (P_{hjt}), display (D_{hjt}), and feature (F_{hjt}) covariates that the household faces, regardless of whether the household purchases in the cola category. Our econometric approach models the multinomial outcome y_{ht} as explained next.

Let U_{hjt} denote the (indirect) utility of household h for brand j at shopping trip t . We assume that we can express this utility as a function of the entire set of brand-specific covariates, $(P_{hjt}, D_{hjt}, F_{hjt})$, as well as the household's lagged brand choice outcome, which represents the brand that was most recently purchased by the household, also referred to as the household's *state variable*, s_{ht} , as follows.

$$U_{hjt} = \alpha_{hj} + \beta_{1h} * P_{hjt} + \beta_{2h} * D_{hjt} + \beta_{3h} * F_{hjt} + \lambda_h * I[S_{ht} = j] + \varepsilon_{hjt}, \quad (1)$$

where α_{hj} , $j = 1, 2, \dots, J$, are the household's brand intercepts, $\beta_h = (\beta_{1h}, \beta_{2h}, \beta_{3h})$ are the household's marketing mix sensitivities, $I[A]$ is the indicator function that takes the value of 1 when event A occurs and the value of 0 otherwise, S_{ht} represents the household's previously purchased brand in the category, and λ_h is the household-specific inertia parameter.²¹ We assume

²¹ This coefficient is more generally referred to as the *state dependence coefficient*, and captures inertia only when it takes positive values; it captures variety seeking when it takes negative values. In this paper, we will refer to the

that the random errors $\varepsilon_{ht} = (\varepsilon_{h1t}, \varepsilon_{h2t}, \dots, \varepsilon_{hJt})$ are distributed *iid* Gumbel with location 0 and scale 1.

Let U_{h0t} denote the (indirect) utility of household h for the no-purchase option (also called “outside good”) 0 at shopping trip t . We assume that we can express this utility as follows.

$$U_{h0t} = \varepsilon_{h0t}. \quad (2)$$

We assume that the random error ε_{h0t} is distributed *iid* Gumbel with location 0 and scale 1.

We determine the multinomial outcome y_{ht} in the usual way: by the principle of maximum utility. We observe the outcome $y_{ht} = j$ when the utility of the j^{th} option to the household exceeds that of the remaining options. This yields the following probabilistic model for brand choice.

$$P_{hjt} = \frac{e^{\alpha_{hj} + \beta_{1h} * P_{hjt} + \beta_{2h} * D_{hjt} + \beta_{3h} * F_{hjt} + \lambda_h * I[S_{ht} = j]}}{1 + \sum_{k=1}^J e^{\alpha_{hk} + \beta_{1h} * P_{hkt} + \beta_{2h} * D_{hkt} + \beta_{3h} * F_{hkt} + \lambda_h * I[S_{ht} = k]}} \quad (3)$$

which has the familiar Multinomial Logit (MNL) functional form. This inertial demand model, which has been used, for example, by Seetharaman, Ainslie and Chintagunta (1999), captures inertia as a *first-order* behavioral phenomenon, i.e., only the household’s most (and not the second-most, third-most etc.) recent brand choice influences its current brand choice probabilities. This assumption is reasonable given that past research in packaged goods categories has demonstrated that higher-order lagged brand choices capture little additional explanatory variance beyond the most recent lagged choice outcome, in terms of explaining

state dependence coefficient as the *inertia parameter* for expositional convenience since it only takes positive values in our cola dataset.

current brand choices of consumers (see, for example, Kahn, Kalwani and Morrison 1986, Seetharaman 2003 etc.).

The objective of the empirical analysis is to estimate the parameters $\Psi = (\{\alpha_{hj}, j = 1, 2, \dots, J\}, \{\beta_h = (\beta_{1h}, \beta_{2h}, \beta_{3h})\}, \lambda_h)$ for each of H households.

Following the latent class approach of Kamakura and Russell (1989), we assume that households belong to M segments. This simplifies our empirical objective to estimating the parameters Ψ for each of M segments (rather than H households), as well as the associated segment sizes. This is done by maximizing the following sample log-likelihood function (which has a convenient closed-form expression).²²

$$\ln L = \sum_{h=1}^H \ln \left(\sum_{m=1}^M \pi_m * \left[\prod_{t=1}^{T_h} \prod_{j=1}^J \{P_{mjt}\}^{Y_{hjt}} \right] \right), \quad (4)$$

where $\pi_m \in [0, 1]$ stands for the size of segment m , and P_{mjt} is the conditional MNL probability (obtained by replacing subscript h with subscript m in equation (4)) of household h buying brand j at shopping trip t , given that household h belongs to segment m . Since households usually undertake shopping trips at weekly intervals, we will interchangeably use t , for expositional purposes, to refer to shopping trip or week.

²² Unlike the random coefficients logit model, the latent class logit model yields convenient closed-form expressions for aggregate-level brand demand functions (as will be explained in the next section). Further, Andrews, Ainslie and Currim (2002) show that the latent class logit model yields aggregate estimates of brand demand, as well as holdout demand forecasts, that are just as accurate as those yielded by random coefficients logit models.

2.4 Structural Econometric Model of Dynamic Distribution Channel

Pricing in the Presence of Inertial Demand

To develop a structural econometric model of distribution channel pricing in the cola category, we recognize that each manufacturer j ($j = \text{Coke}, \text{Pepsi}$) sets a wholesale price for a retailer, while the retailer then sets a retail price, for their brand, during each of $t = 1, 2, \dots, T$ weeks in the data.²³ The retailer is a monopolist in a local market. During each week, we observe an outcome variable $P_{jt} > 0$ for each brand. Our econometric approach models the continuous outcome P_{jt} as explained next. We do this in two steps. We first derive a predictive model of aggregate-level brand demand, which is an aggregation of individual-level brand demand, as derived in the previous section. We then embed this predictive model of aggregate-level brand demand within a dynamic pricing game within a distribution channel involving competing manufacturers and a common retailer. This dynamic pricing game assumes that manufacturers engage in Bertrand price competition with each other while setting their wholesale prices, while the retailer plays the role of a Stackelberg follower while setting retail prices for the manufacturers' brands (taking their wholesale prices as given).

2.4.1 Predictive Model of Aggregate-Level Brand Demand

Let S_{jt}^m denote a *state variable* that represents the (segment-specific) *installed base* for brand j during week t . This installed base variable represents the number of consumers in segment m , as of week t , whose most recent brand choice in the cola category is brand j . Further, let $S_t^m = (S_{1t}^m, S_{2t}^m, \dots, S_{Jt}^m)$ represent the vector of installed base variables across all J brands during

²³ While there are 4 brands – Coke, Pepsi, Royal Crown, and Private Label – in the cola category, we endogenize the prices of only the two major brands – Coke, Pepsi – in the empirical analysis. This is done for computational convenience. The prices of Royal Crown and Private Label are treated as exogenous to the analysis.

week t . The following equation, called the *state equation*, captures the evolution of the state variable, S_{jt}^m , from week t to week $t+1$.

$$S_{j,t+1}^m = \sum_{k \neq j}^J S_{kt}^m * \Pr_t^m(k \rightarrow j) + S_{jt}^m * \left(1 - \sum_{k \neq j}^J \Pr_t^m(j \rightarrow k) \right), \quad (5)$$

where $\Pr_t^m(k \rightarrow j)$ stands for the *switching probability*, for a consumer in segment m , of switching from brand k to brand j , during week t , and is given by

$$\Pr_t^m(k \rightarrow j) = \frac{e^{\alpha_{mj} + \beta_{1m} * P_{hjt} + \beta_{2m} * D_{hjt} + \beta_{3m} * F_{hjt}}}{1 + e^{\alpha_{mk} + \beta_{1m} * P_{hkt} + \beta_{2m} * D_{hkt} + \beta_{3m} * F_{hkt} + \lambda} + \sum_{l \neq k}^J e^{\alpha_{ml} + \beta_{1m} * P_{hlt} + \beta_{2m} * D_{hlt} + \beta_{3m} * F_{hlt}}}. \quad (6)$$

Equation (5) represents how the installed base of brand j changes from week t to week $t+1$. This happens in two ways (as represented by the two terms on the right-hand side of the equation): one, customers currently in the installed bases of the other brands (S_{kt}^m) switch to the installed base of brand j by buying brand j in week t , which happens with probability $\Pr_t^m(k \rightarrow j)$, as shown in equation (6); two, customers currently in the installed base of brand j (S_{jt}^m) continue being in the installed base of brand j , by either repeat-purchasing brand j , or choosing the no-purchase option, in week t , with the collective probability of the two events being $1 - \sum_{k \neq j}^J \Pr_t^m(j \rightarrow k)$.

Given the state equation (5) governing the evolution of the state variable, S_{jt}^m , aggregate-level brand demand for brand j in week t , D_{jt} , is given by

$$D_{jt} = \sum_{m=1}^M \pi_m * D_{jt}^m, \quad (7)$$

where D_{jt}^m stands for segment-level demand for brand j in week t in segment m , and is given by

$$D_{jt}^m = \sum_{k=1}^J S_{kt}^m * \Pr_t^m(k \rightarrow j). \quad (8)$$

This completes our discussion of the predictive model of aggregate brand-level demand. In summary, aggregate brand-level demand for brand j in week t is predicted using equation (7), which, in turn requires equation (8) as an input, which, in turn, requires equations (5) and (6) as inputs. The unknown parameters in these equations – which include all parameters in equation (6), as well as the parameter \square_m in equation (7) -- are estimated using household-level scanner panel data, as explained in the previous section.

2.4.2 Markov-Perfect Equilibrium of the Dynamic Pricing Game

Let C_{jt} denote the marginal cost of the manufacturer for brand j during week t . It is written as

$$C_{jt} = C_j + v_{jt}, \quad (9)$$

where C_j stands for a time-invariant marginal cost component (such as average production cost), and v_{jt} is a time-varying cost shock (due to time-varying supply shocks, changes in raw material prices etc.) that is known to the manufacturers (but not to the researcher). We assume that v_{jt} is *iid* $N(0, \sigma_j^2)$ across all j and t . Let $v_t = (v_{1t}, v_{2t}, \dots, v_{Jt})'$.

We assume a discrete-time, infinite-horizon framework (with $t = 1, 2, \dots, \infty$), with manufacturers making simultaneous wholesale pricing decisions in each period (week), and playing a repeated Bertrand game with discounting. Given wholesale price W_{jt} and retail prices $P_t = (P_{1t}, P_{2t}, \dots, P_{Jt})'$, the manufacturer's single-period profit in period t is given by

$$\Pi^j(W_t, P_t, S_t, v_t) = (W_{jt} - C_j - v_{jt}) * D_j(P_t, S_t). \quad (10)$$

We assume that the retailer's marginal cost of selling each unit of brand j in period t is equal to the wholesale price of the brand, W_{jt} .²⁴ We assume that the retailer chooses retail prices in each period, taking wholesale prices as given. The retailer's single-period profit in period t is given by

$$\Pi^R(W_t, P_t, S_t, v_t) = \sum_{k=1}^J (P_{kt} - W_{kt}) * D_k(S_t, P_t). \quad (11)$$

During week t , each manufacturer is assumed to choose the wholesale price for their brand, W_{jt} , with the objective of maximizing the discounted present value of their *brand profit*, while the retailer is assumed to choose the retail prices of all brands, P_{jt} , with the objective of maximizing the discounted present value of *category profit*, over an infinite horizon. On account of inertial demand, these current prices, W_{jt} and P_{jt} , will not only influence the current demands of brands, D_{jt} , but also change the installed bases of all brands in all consumer segments, S_{jt}^m , which, in turn will affect the future stream of profits of, as well as future strategic interactions among, the manufacturers and the retailer. All channel members are assumed to have full information about the current installed bases of all brands in all consumer segments, $S_t \equiv (\{S_{1t}^m, \dots, S_{jt}^m\}; m=1, \dots, M) \in \mathcal{S}$, as well as the current cost shocks associated with all brands, $v_t \in Z$, before making their pricing decisions. The observed (by the researcher) state vector, S_t , evolves according to the state equation (5) given earlier. In this set-up, the cost shocks of manufacturers, v_t , do not affect the observed states, S_t , directly. Instead, the cost shocks, v_t , have transitory effects on manufacturers' payoffs, as well as the retailer's payoff, by affecting

²⁴ This is a standard assumption in the literature. Other components of marginal costs, such as inventory holding costs, can be considered as relatively minor when compared to the wholesale prices.

their pricing decisions. In other words, as in Rust (1987), we assume that the observed states, S_t , and unobserved states, v_t , are conditionally independent.

Conditional on the current states, S_t and v_t , the retailer is assumed to maximize the expected discounted sum of single-period category profits,

$$E \left[\sum_{k=t}^{\infty} \rho^{k-t} * \Pi^R(P_k, W_k, S_k, v_k) | S_t, v_t \right], \quad (12)$$

while the manufacturer is assumed to maximize the expected discounted sum of single-period brand profits.

$$E \left[\sum_{k=t}^{\infty} \rho^{k-t} * \Pi^j(P_k, W_k, S_k, v_k) | S_t, v_t \right], \quad (13)$$

where the expectation is taken over all the other channel members' current actions, all future values of observed and unobserved states, and all future actions of all channel members. We also assume that the manufacturers and the retailer have a common discount factor $\rho < 1$.

We focus our attention on Pure-Strategy Markov-Perfect Equilibria (MPE), noting that there could be multiple such equilibria. In our case, a Markov strategy for a channel member describes their pricing strategy for week t – wholesale or retail, depending on whether manufacturer or retailer -- as a function of current states, S_t and v_t . Formally, the retailer's strategy can be written as $\sigma_R : S \times Z \rightarrow P \in \mathbb{R}^J$, where $P = (P_1, P_2, \dots, P_J)'$ is the vector of retail prices, while each manufacturer's strategy can be written as $\sigma_j : S \times Z \rightarrow W_j \in \mathbb{R}$, where W_j is the wholesale price charged by manufacturer j . A Markov profile $\sigma = \prod_{j=1}^{J+1} \sigma_j$, which is defined

as $\sigma : S \times Z \rightarrow (P, W)$, is an MPE if there is no channel member i (retailer or manufacturer) who

prefers an alternative strategy σ_i' over σ_i , when all other channel members are choosing their strategies according to σ_{-i} . This can be formally written as follows.

$$V_i(S, \nu | \sigma_i, \sigma_{-i}) \geq V_i(S, \nu | \sigma_i', \sigma_{-i}), \forall i, \forall S, \forall \sigma_i', \quad (14)$$

Given that the behavior is a Markov profile, for each manufacturer j , the discounted sum of profits can be written in the form of the following Bellman equation.

$$V_j(S, \nu) = \sup_{W_j} \left\{ (W_j - C_j - \nu_j) * D_j(S, P) + \rho * \int V_j(S' | S, P) dF(\nu') \right\}, \quad (15)$$

Similarly, the retailer's discounted sum of profits can be written as the form of the following Bellman equation.

$$V_R(S, \nu) = \sup_{P_1, P_2, \dots, P_J} \left\{ \sum_{k=1}^J (P_k - W_k) * D_k(S, P) + \rho * \int V_R(S' | S, P) dF(\nu') \right\}. \quad (16)$$

It is useful to note that the payoff relevant states for the retailer are (S, ν) , which are identical to those for each manufacturer. While the retailer's pricing decisions are directly influenced only by manufacturers' wholesale prices, since the manufacturers' wholesale prices are functions of S and ν , the value function of the retailer is a function of (S, ν) .

2.4.3 Estimation Challenges

The objective of the estimation is to estimate the parameters ($\{C_j, \square_j\} j = 1, 2, \dots, J$). The biggest challenge for the researcher is that wholesale prices are unobserved, but as manufacturers' wholesale pricing policies will determine the retailer's retail pricing policy, if the retailer's continuation value in equation (16) is known, under the Stackelberg assumption, one can invert unobserved wholesale prices by using the retailer's optimality conditions for setting retail prices. Similarly, if each manufacturer's continuation value in equation (15) is known,

under the Bertrand assumption, one can invert unobserved manufacturer costs by using the manufacturer's optimality conditions for setting wholesale prices. Thereafter, putting the retailer's and manufacturers' value functions together, and by jointly exploiting the optimality conditions of the retailer and the manufacturer (which gets rid of the unobserved wholesale prices since they cancel out), one can infer the marginal costs of the manufacturers using observed retail prices. This estimation strategy is adopted in Sudhir (2001). Such a strategy is facilitated by the authors' assumptions that there are no unobserved structural cost shocks for manufacturers, and that the channel members maximize their profits over a finite number (i.e., three) of periods. Neither assumption holds in our case. We allow for structural cost shocks, ν , as well as assume that manufacturers and the retailer maximize infinite-period expected profits. This results in the value functions of the retailer and the manufacturers not having a closed form in our case, which makes the estimation strategy of Sudhir (2001) inapplicable.

Since the continuation values in equations (15) and (16) are not known, one needs to compute the continuation values of the dynamic game for each candidate cost structure. There are two estimation methods that have been previously developed for multi-agent problems, such as ours, and have become well-established in the literature. These are the nested fixed point algorithm of Pakes and McGuire (1994) and the two-step algorithm of Bajari, Benkard and Levin (2007). We briefly discuss these two methods next, and then explain why they are not suitable for our needs, before proceeding to describe our proposed estimation method.

First, let us start with the nested fixed point algorithm (NFXP, Rust 1987), which represents the classical approach to estimating dynamic decision problems. This algorithm relies on the idea that optimal prices can be obtained by finding the fixed point of the value function (a functional equation) in the Bellman equation, i.e., by locating a function such that the right-hand

and left-hand sides of the Bellman equation become equal. The Pakes and McGuire (1994) algorithm, which uses the nested fixed point algorithm in a multi-agent context, allows us to accurately calculate optimal dynamic policies without having to use the data, conditional on given parameters. However, the major limitation of this algorithm is its computational burden, which we explain next.

In order to estimate the set of structural parameters that rationalizes the observed pricing outcomes in our data, we would need to search for the fixed points which represent the optimal policies for different combinations of state variables in a numerical search routine, and repeat the procedure until we get a close match between the computed and observed prices. That is, conditional on model parameters, we must compute the MPE for all channel members. The algorithm requires us to iterate over σ_j many times until the best response function is satisfied. In our case, the fixed point search must account for both horizontal (among manufacturers) as well as vertical (between manufacturers and the retailer) interactions among agents, which increases the computational burden. Even more strikingly, with large dimensions of the state space, such as in our case (with two manufacturers and a retailer, as well as two consumer segments), the curse of dimensionality problem becomes severe. Additionally, there is no recommended way of choosing an equilibrium in the case of multiple equilibria, which often arise in multi-agent problems.²⁵ Furthermore, the convergence of the equilibrium strategy, σ , is also not guaranteed under the Pakes and McGuire (1994) algorithm since it is not a contraction mapping. For this reason, adapting the NFXP algorithm to estimate our dynamic game presents a non-trivial challenge.

²⁵ In the existing empirical literature on dynamic games, it is argued that the GMM estimation method solves the multiple equilibria problem because the data can be used to tell which equilibrium is actually chosen by the players. However, since wholesale prices are unobserved in our case, which of several wholesale price equilibria applies cannot be determined using the data.

The computational burden associated with the NFXP algorithm can be mitigated using the two-step approach of Hotz and Miller (1993), which has been suitably extended for multi-agent problems by Bajari, Benkard and Levin (2007). Under this approach, the policy functions of agents are *estimated* for various points in the state space using the observed data. With the estimated policy functions and state transitions, one can calculate the values of the agents, for a given set of structural parameters, using the idea of forward simulation, which was first proposed by Hotz, Miller, Sanders and Smith (1994). However, this approach is inapplicable in our case since wholesale prices of manufacturers are unobserved in the data which makes it impossible to estimate the wholesale price policy functions of the manufacturers.

To summarize, there exists no estimation approach in the literature that can be suitably modified to handle the estimation of our proposed dynamic pricing model for the distribution channel. In this paper, therefore, we develop a new estimation method that can handle both the existence of unobserved actions of agents (i.e., manufacturers' wholesale prices, in our case), as well as a high-dimensional state space (with two manufacturers and a retailer, as well as two consumer segments). We describe our estimation method next.

2.4.4 Proposed Estimation Method for the Dynamic Pricing Game

Under the MPE assumption, optimal actions of the manufacturers are functions of payoff relevant states. We approximate the policies of manufacturers and the retailer using a parametric polynomial function of observed and unobserved states. With the parameterized policy functions, we can forward simulate the value functions. Our estimation strategy is to search for the parameters of policy functions and structural parameters through one numerical search routine, by minimizing a criterion function based on moment conditions, together with a penalty function if the optimality conditions are not satisfied. At true structural parameters, it is required that our

parametric policy functions are consistent with the policies from the data, and the parametric policy functions satisfy the first-order conditions.

The objective of the estimation is to estimate the parameters $(\{C_j, \square_j\} j = 1, 2, \dots, J)$. We parameterize the retailer's retail pricing policies for brands as flexible functions of state variables, S and ν , as shown below.

$$P_j = \hat{P}_j(S, \nu | \theta_j^R), \quad (17)$$

where $\hat{P}_j(\cdot)$ denotes the parametric approximation of the optimal retail policies of the retailer, and θ_j^R is a vector of parameters characterizing this flexible function. We also parameterize manufacturers' wholesale pricing policies as flexible functions of state variables, S and ν , as shown below.

$$W_j = \hat{W}_j(S, \nu | \theta_j^M), \quad (18)$$

where $\hat{W}_j(\cdot)$ denotes the parametric approximation of the optimal wholesale pricing policies of manufacturer j , and θ_j^M is a vector of parameters characterizing this flexible function.

Given the policy functions in equations (17) and (18), as well as the structural parameters (which yield the transition probabilities for state variables S and ν), the expected continuation values, $E_{\nu'} V_j(S') = \int V_j(S' | S, P) dF(\nu')$ and $E_{\nu'} V_R(S') = \int V_R(S' | S, P) dF(\nu')$, which are represented by the second terms on the right-hand side of equations (15) and (16) respectively, can be computed using forward simulation (see Appendix 1 for details).

We take the derivative of the value function of the retailer in equation (16) with respect to retail price P_j in order to construct the first-order conditions for the retailer, as shown below.

$$F_j = \frac{\partial V_R(S, \nu)}{\partial P_j} = D_j + \sum_{k=1}^J (P_k - W_k) * \frac{\partial D_k}{\partial P_j} + \rho * \frac{\partial E_{\nu} V_R(S')}{\partial P_j} = 0. \quad (19)$$

This first-order condition of the retailer is different from that which corresponds to myopic profit maximization on account of the last term, i.e., $\rho * \frac{\partial E_{\nu} V_R(S')}{\partial P_j}$. This term captures the influence of the current retail price, P_j , on the next period's state, S' , and, therefore, on the expected continuation value, $E_{\nu} V_R(S')$, of the next period. In the absence of this term, the only effect of inertia in demand will be reflected in the second term, $\sum_{k=1}^J (P_k - W_k) * \frac{\partial D_k}{\partial P_j}$. The derivative, with respect to retail price, of the expected continuation value of the next period, $\frac{\partial E_{\nu} V_R(S')}{\partial P_j}$, can be obtained using chain rule, as shown below.

$$\frac{\partial E_{\nu} V_R(S')}{\partial P_j} = \frac{\partial E_{\nu} V_R(S')}{\partial S'} * \frac{\partial S'(S, P)}{\partial P_j}. \quad (20)$$

Rearranging terms, we can write the first-order condition for retail price such that it expresses the retailer's optimal retail price for a brand as a function of S and ν , as shown below.

$$P_j^*(S, \nu) = W_j - \left\{ D_j + \sum_{k \neq j} (P_k - W_k) * \frac{\partial D_k}{\partial P_j} + \rho * \frac{\partial E_{\nu} V_R(S')}{\partial P_j} \right\} * \left[\frac{\partial D_j}{\partial P_j} \right]^{-1}. \quad (21)$$

If the retail pricing policy function in equation (17) is optimal, for any given set of state variables, (S, ν) , the computed retail prices should match the retail prices from the above equation, after allowing for approximation error due to the parametric policy functions, as shown below.

$$P_j^*(S, \nu) \cong \hat{P}_j(S, \nu | \theta_j^R) \quad (22)$$

We take the derivative of the value function of the manufacturer in equation (15) with respect to wholesale price W_j in order to construct the first-order conditions for the manufacturer, as shown below.

$$\frac{\partial V_j(S, \nu)}{\partial W_j} = D_j + (W_j - C_j - \nu_j) * \left\{ \sum_{k=1}^J \frac{\partial D_j}{\partial P_k} * \frac{\partial P_k}{\partial W_j} \right\} + \rho * \sum_{k=1}^J \frac{\partial E_{\nu'} V_j(S')}{\partial P_k} * \frac{\partial P_k}{\partial W_j} = 0. \quad (23)$$

This first-order condition of the manufacturer is different from that which corresponds to myopic profit maximization on account of the last term, i.e., $\rho * \sum_{k=1}^J \frac{\partial E_{\nu'} V_j(S')}{\partial P_k} * \frac{\partial P_k}{\partial W_j}$. This term captures the influence of the current wholesale price, W_j , on the next period's state, S' , and, therefore, on the expected continuation value, $E_{\nu'} V_j(S')$, of the next period. In the absence of this term, the only effect of inertia in demand will be reflected in the second term, $(W_j - C_j - \nu_j) * \left\{ \sum_{k=1}^J \frac{\partial D_j}{\partial P_k} * \frac{\partial P_k}{\partial W_j} \right\}$. The derivative, with respect to retail price, of the expected continuation value of the next period, $\frac{\partial E_{\nu'} V_j(S')}{\partial P_k}$, can be obtained using chain rule, as shown below.

$$\frac{\partial E_{\nu'} V_j(S')}{\partial P_k} = \frac{\partial E_{\nu'} V_j(S')}{\partial S'} * \frac{\partial S'(S, P)}{\partial P_k}. \quad (24)$$

Rearranging terms, we can write the first-order condition for wholesale price such that it expresses the manufacturer's optimal wholesale price for a brand as a function of S and ν , as shown below.

$$W_j^*(S, \nu) = C_j + \nu_j - \left[D_j + \rho * \sum_{k=1}^J \frac{\partial E_\nu V_j(S')}{\partial P_k} * \frac{\partial P_k}{\partial W_j} \right] \left\{ \sum_{k=1}^J \frac{\partial D_j}{\partial P_k} * \frac{\partial P_k}{\partial W_j} \right\}^{-1}. \quad (25)$$

The above equation involves the retailer's retail pricing responses to manufacturers' wholesale price changes, i.e., $\partial P / \partial W$. We take the derivative of the retailer's first-order condition, F_j (see equation 19), with respect to all of the J retail prices (dP_1, \dots, dP_J) and with respect to a single wholesale price W_j , with variation dW_j . The following equation system can be derived.

$$\begin{aligned} F_{j1}dP_1/dW_1 + F_{j2}dP_2/dW_1 + \dots + F_{jJ}dP_J/dW_1 &= \partial D_1 / \partial P_j \\ F_{j1}dP_1/dW_2 + F_{j2}dP_2/dW_2 + \dots + F_{jJ}dP_J/dW_2 &= \partial D_2 / \partial P_j \\ \vdots & \\ F_{j1}dP_1/dW_J + F_{j2}dP_2/dW_J + \dots + F_{jJ}dP_J/dW_J &= \partial D_J / \partial P_j \end{aligned}, \quad (26)$$

where $F_{ij} = \partial^2 V_R(S, \nu) / \partial P_i \partial P_j$.

We can represent the above $J \times J$ total derivatives in matrix form as follows

$$\frac{dP}{dW} = F^{-1} A, \quad (27)$$

where the $[j, i]^{\text{th}}$ elements of the above matrices are as shown below.

$$\frac{dP}{dW} [j, i] = \frac{\partial P_j}{\partial W_i}, \quad F[j, i] = F_{ji}, \quad A[j, i] = -\frac{\partial D_i}{\partial P_j} \text{ for } i, j = 1, 2, \dots, J. \quad (28)$$

Substituting from equations (27) and (28) in to equation (25), we obtain the manufacturer's optimal wholesale pricing policy function. If the wholesale pricing policy function in equation (18) is optimal, for any given set of state variables, (S, ν) , the computed wholesale prices should match the wholesale prices from equation (25), after allowing for approximation error due to the parametric policy functions, as shown below.

$$W_j^*(S, \nu) \cong \widehat{W}_j(S, \nu | \theta_j^M). \quad (29)$$

In order to recover the structural parameters of interest i.e., C_j and σ_j , we construct the following two moment conditions.

$$E[\nu_j | S] = 0, E[\nu_j^2 | S] - \sigma_j^2 = 0, \quad (30)$$

where ν_j is obtained using the optimality conditions of the retailer and the manufacturers, i.e., equations (21) and (25), as shown below.

$$\begin{aligned} \nu_j = P_j - C_j + & \left\{ D_j + \sum_{k \neq j} (P_k - W_k) * \frac{\partial D_k}{\partial P_j} + \rho * \frac{\partial E_{\nu} V_R(S')}{\partial P_j} \right\} * \left[\frac{\partial D_j}{\partial P_j} \right]^{-1} \\ & + \left[D_j + \rho * \sum_{k=1}^J \frac{\partial E_{\nu} V_j(S')}{\partial P_k} * \frac{\partial P_k}{\partial W_j} \right] * \left\{ \sum_{k=1}^J \frac{\partial D_j}{\partial P_k} \frac{\partial P_k}{\partial W_j} \right\}^{-1}. \end{aligned} \quad (31)$$

The GMM estimator, as applied in the literature, typically relies on the first moment. In our case, in order to identify the cost shock variance parameter, σ_j , we additionally use the second moment, as shown in equation (30). A second point of departure of our estimation approach from the GMM estimator that is typically used in the literature lies in equations (22) and (29). Given a set of state variables, (S_q, ν_q) , $q = 1, \dots, S$, our estimates are obtained by minimizing not only a criterion function that is based on the moment conditions in equation (31), but also the following two “penalty” functions.

$$\begin{aligned} & \sum_{q=1}^S [P_j^*(S_q, \nu_q) - \widehat{P}_j(S_q, \nu_q | \theta_j^R)]^2, \\ & \sum_{q=1}^S [W_j^*(S_q, \nu_q) - \widehat{W}_j(S_q, \nu_q | \theta_j^M)]^2, \end{aligned} \quad (32)$$

At the true policy functions and true values of model parameters, the errors associated with the moment conditions in equation (31), as well as the approximation errors in equation (32), will be minimized.

Our estimation approach is similar to the recently proposed estimation method in Cosguner, Chan and Seetharaman (2012), except for the additional second penalty function in equation (32), which is based on the difference between the polynomial approximation of the wholesale price and the optimal wholesale price that is implied by the first-order condition. This renders the estimation computationally much more manageable when compared to the NFXP method.

The asymptotic distribution of our estimator is difficult to derive and even if it has a closed form, it is likely to be difficult to calculate (as in BBL). Furthermore, we have to account for the estimation error in the estimated demand function. Therefore, we use the following bootstrapping procedure to calculate the standard errors:

1. We draw θ^{Ds} , $s = 1, 2, \dots, ns$, from the asymptotic normal distribution of the demand model parameter estimates, $N(\hat{\Theta}^D, \hat{\Sigma}^D)$, where $\hat{\Theta}^D$ stands for the estimated demand parameters, and $\hat{\Sigma}^D$ stands for the estimated covariance matrix of the estimated demand parameters (which accounts for the estimation error in the demand function).
2. We obtain bootstrapped data, $(P_t^s, S_t^s, s = 1, 2, \dots, ns)$, by drawing independent, random samples, with replacement, from the original data.
3. We re-estimate the parameters of the structural econometric model of dynamic channel pricing for each bootstrapped draw of the original data (from Step 2 above), while generating the evolution of states, S , as well as the demand function, D , based

on each bootstrapped draw of the estimated demand model parameters (from Step 1 above).

4. Using the estimated pricing model parameters from Step 3 above, across all bootstrapped draws, we calculate the standard errors associated with those estimates.

Below, we summarize the benefits of our proposed estimation method for multi-agent dynamic decision problems.

1. It allows the researcher to invert actions that are unobserved in the data, as is typically done in static decision problems, by inverting them from the optimality conditions;
2. It allows the researcher to model situations with multiple unobserved states entering the policies of economic agents;
3. It allows the researcher to calculate optimal dynamic policies without relying on large amount of data;
4. It uses the forward simulation idea to yield significant computational gains.

Since our methodology relies on first-order conditions from the Bellman equation, it is designed specifically for problems with continuous policies such as pricing, advertising, R&D investment etc. For problems involving both continuous and discrete (e.g., entry and exit) policies, one can use a hybrid algorithm that uses inequality constraints for discrete actions, together with the first order conditions for continuous actions. To further decrease the computational burden, the numerical search routine should start with a good set of initial values. For example, one can start with the parameters from the static counterpart of the dynamic game. Since the parameters from the static game may be fairly close to the dynamic counterpart, it reduces the convergence time of the numerical search routine significantly. Another issue concerns how to flexibly model the pricing policy functions. Employing a high-order polynomial

approximation may lead to too many estimable parameters, especially when the dimensionality of the state space is large. Therefore, we start with a low-order (e.g., linear) polynomial, and then gradually increase the order of the polynomial until the optimal and the parametric policy functions closely match each other.

We conduct a series of Monte Carlo simulations in order to study how well our proposed estimation approach can recover the model parameters under a wide range of assumed structural parameters, i.e., high versus low average cost, high versus low cost shock, using a sample size similar to ours. We also allow for monopoly versus duopoly manufacturer scenarios, as well as presence versus absence of the retailer, in the simulation. Under each tested case in our simulations, we find that the estimates of C_j and σ_j and are very close to their true (assumed) values. The results are reported in Appendix 3. This Monte Carlo simulation exercise gives us confidence regarding the efficiency of our proposed estimator.

2.5 Empirical Results

We use scanner panel data from Information Resources Incorporated's (IRI) scanner-panel database on cola purchases of 356 households making 32942 shopping trips at a supermarket store in a suburban market of a large U.S. city. The dataset covers a two-year period from June 1991 to June 1993. The supermarket is a local monopolist in the sense of not having other supermarkets nearby and, therefore, drawing a loyal core group of shoppers to the same store for their grocery shopping. Table 1.1 presents some descriptive statistics on weekly marketing variables and market shares of four major cola brands in the data. The 356 households are observed to purchase cola during 5784 (17.56%) of their shopping trips. In terms of average prices, we see that Coke, Pepsi and Royal Crown occupy a high price-tier, while the Private Label occupies a low price-tier, at the store. In terms of display and feature promotions, we see that Pepsi is displayed and featured more frequently than the other brands by the retailer. In terms of average weekly market shares, Pepsi is observed to be the dominant cola brand (with an average market share of 0.4567), while the Private Label is the smallest brand (with an average market share of 0.0685).

2.5.1 Estimation Results for the Inertial Demand Model

Table 1.2 presents the estimates of the inertial demand model under the 2-support heterogeneity specification (which is reported, as well as used as an input for the dynamic pricing model, for expositional convenience).²⁶ As far as the brand intercepts are concerned, we find that the private label has the smallest -- most negative -- value of the estimated brand intercept among the four brands in both segments. This suggests that the private label brand

²⁶ Substantive insights gleaned from our empirical analysis remain similar when the heterogeneity specification is modified to include additional supports for the heterogeneity distribution. These results are available upon request.

enjoys the lowest baseline preference in the cola market, which is not surprising considering that private label brands typically draw sales on account of their lower prices, as opposed to their relative intrinsic attractiveness, when compared to other (national) brands. Pepsi is found to have the highest baseline preference among the four brands in both segments, while Coke has the second highest baseline preference. This is consistent with the institutional reality that Pepsi was the dominant cola brand in supermarket stores (even though Coke had higher overall national market share) in the US during the 1990s.

As far as the marketing mix coefficients are concerned, the estimated price coefficient is negative, as expected, while estimated display and feature coefficients are positive, as expected, for both segments. Between the two segments, segment 2 (the larger segment, containing 71 % of the households) is found to be more price-sensitive (price coefficient of -6.727 versus -5.233), more display-sensitive (display coefficient of 1.454 versus 1.113), and more feature-sensitive (feature coefficient of 0.320 versus 0.228), than segment 1.

As far as the estimated inertia coefficients are concerned, they are positive for both segments. This implies that after controlling for the effects of a household's intrinsic brand preferences and their responsiveness to the marketing activities of brands, the household's probability of buying the previously purchased brand is higher than the household's probability of buying any of the remaining brands. The estimated inertia parameters translate to switching costs -- which can be interpreted as the price premium that a brand can charge in the current week to a consumer who bought that same brand last time, relative to a consumer who bought another brand last time -- of \$0.30 and \$0.13 in segments 1 and 2, respectively. These are substantively significant; given the average prices of cola brands (see Table 1.1).

2.5.2 Estimation Results for the Structural Econometric Model of Dynamic Pricing in the Distribution Channel in the Presence of Inertial Demand

Table 2.1 presents the estimated marginal costs of production, along with the estimated standard deviations of the cost shocks, for Coke and Pepsi under the proposed structural econometric model of dynamic pricing in the distribution channel. Given the average retail prices of Coke and Pepsi in Table 1.1, the estimated costs of \$0.436 and \$0.355 translate to estimated channel profit margins of \$0.369 (85 %) and \$0.395 (111 %) for Coke and Pepsi, respectively. These costs are in the ball-park of published estimates of marginal costs in this industry during that period (see, for example, Yoffie 1994), and lend face validity to our estimates.

2.6 Managerial Implications

In order to understand the substantive implications of our estimated structural econometric model of dynamic pricing, we use the estimated structural parameters for the proposed dynamic pricing model (from Table 2.1) and compute the resulting equilibrium wholesale and retail prices for Coke and Pepsi. We compare these prices to those that would result from myopic pricing (which ignores the investing incentive) by setting the discount factor for all channel members to 0. Additionally, we compare the prices to those that would result from static pricing (which ignores both the investing and harvesting incentives) which not only sets the discount factor for all channel members to 0 (as in myopic pricing) but also sets the inertia parameter to zero. The results of these computations are reported in Table 2.2. Under static pricing, the equilibrium profit margins of Coke and Pepsi are \$0.1939 (31%) and \$0.1909 (35%), respectively, for the retailer, and \$0.1839 (42%) and \$0.1894 (53%), respectively, for the manufacturers. Under myopic pricing, the equilibrium profit margins of Coke and Pepsi are \$0.2128 (33%) and \$0.2163 (37%), respectively, for the retailer, and \$0.2066 (47%) and \$0.2293 (65%), respectively, for the manufacturers. Under dynamic pricing, the equilibrium profit margins of Coke and Pepsi are \$0.2139 (38%) and \$0.2151 (42%), respectively, for the retailer, and \$0.1322 (30%) and \$0.1641 (46%), respectively, for the manufacturers.

The above findings imply that manufacturer profit margins increase by 2.3c (5.2%) and 4c (11.3%) when harvesting incentives are introduced, and decrease by 7.4c (17.1%) and 6.5c (18.4%) when investing incentives are additionally introduced, the net effect being that manufacturers' profit margins are lower than those in the absence of inertia. In other words, the investing incentive dominates the harvesting incentive for the two cola manufacturers, thus yielding equilibrium wholesale prices and, therefore, profit margins that are lower than those in

the absence of inertia. These results validate the analytical implications of the normative pricing models of Chintagunta and Rao (1996), Villas-Boas (2004), Dube, Hitsch and Rossi (2009) and Doganoglu (2010), as well as the results of a counterfactual simulation in Cosguner, Chan and Seetharaman (2012).²⁷

As far as the retailer's profit margins are concerned, they increase by 1.9c and 2.5c when harvesting incentives are introduced, and do not change when investing incentives are additionally introduced, the net effect being that the retailer's profit margins are *higher* than those in the absence of inertia. In other words, the harvesting incentive dominates the investing incentive for the retailer, thus yielding equilibrium retail profit margins for both brands that are higher than those in the absence of inertia. In other words, while the retailer exploits the benefit of the harvesting incentive, by appropriately increasing his retail profit margin, almost equally with the manufacturers, the cost of the investing incentive is borne entirely by the manufacturers. In terms of the net effect of the harvesting and investing incentives on distribution channel profits, we uncover a 3c lowered channel profit margin for Coke, and no change in the channel profit margin for Pepsi (with its 6c increase from harvesting being annulled by a 6c decrease from investing).

In order to understand the role of the retailer on manufacturers' pricing incentives we performed one more counterfactual simulation, in which we simulated the equilibrium policies of manufacturers (without the retailer) under dynamic, myopic and static pricing schemes. Table 2.3 shows that both manufacturers invest significantly less and harvest more without the retailer. The result about the net effect of investing versus harvesting flips for Pepsi (Pepsi starts to

²⁷ None of these mentioned studies allowed for a strategic retailer in the analysis. Our study shows that their implications hold in the presence of a strategic retailer.

harvest more than it invests). Therefore, ignoring the retailer creates a significant bias in order to understand the incentives of manufacturers under inertial demand.

In order to further understand the substantive implications of our estimated structural model of dynamic pricing, we perform two counterfactual simulations. Under each of these simulations, given the estimated structural parameters from our proposed dynamic pricing model, and given the assumed simulation scenario, we compute the optimal prices, under different states, S and v , for the manufacturers. For this purpose, we use the NFXP algorithm of Pakes and McGuire (1994). Computational details are provided in Appendix 2.

2.6.1 Counterfactual Simulation 1: Effects of Increasing Inertia

We have discussed that manufacturers' investing incentives to wholesale pricing dominate harvesting incentives in our data, while the retailer faces only a harvesting incentive and free-rides on the investing costs borne by the manufacturers. However, the relative importance of one incentive compared to the other to all channel members, in general, would depend on the degree of inertia in demand. In this counterfactual simulation, we study how the relative importance of each incentive varies for each manufacturers and the retailer as the degree of inertia in the market varies from low to high. One way of increasing consumer inertia toward cola brands may be to increase reminder advertising in the category using media such as billboards and television (for example, by using catchy jingles, such as "The Real Thing" for Coke, and the "Pepsi Generation" for Pepsi), which increase "top of mind" recall among the installed bases of each brand toward their favored brands and, therefore, make them repeat purchase the favored brands with greater likelihood. We compute the steady-state prices, steady-state demands, as well as steady-state single-period profits, for Coke and Pepsi, at various values of the inertia parameter for one segment at a time. Figures 2.1 and 2.2 present the steady-state

profits of both manufacturers and the retailer as functions of the inertia parameter for segments 1 and 2, respectively. We observe that the profits of all channel members increase as inertia of either segment increases. Specifically, as the inertia parameter of segment 1 (2) increases from 0 to 2, the profits of Coke, Pepsi and the retailer increase by 40 % (13 %), 53 % (54 %), and 135 % (58 %), respectively. As the inertia parameter of segment 1 (2) increases from its existing value of 1.6 (0.9) to 2, the profits of Coke and Pepsi increase by 4 % (10 %), 3 % (37 %), and 28 % (38 %), respectively. These are sizeable increases in profits for all channel members. The relationship between profit and inertia appears to be roughly linear for each cola manufacturer, but convex for the retailer. In other words, the retailer gains disproportionately more from an increasing level of inertia in the cola market.

In order to better elucidate the profit findings in Figures 2.1 and 2.2, we plot the steady-state wholesale and retail prices of both brands as functions of the inertia parameter for segments 1 and 2, respectively, in Figures 2.3 and 2.4. We find in both figures that as inertia increases, the wholesale price of each brand steadily decreases. Specifically, in Figure 2.6 (2.7), Coke's wholesale price decreases from \$0.60 (\$0.58) to \$0.55 (\$0.55), i.e., 9 % (5 %), as the inertia parameter of segment 1 (2) increases from 0 to 2. In the same figure, Pepsi's wholesale price decreases from \$0.52 (\$0.53) to \$0.50 (\$0.50), i.e., 3 % (5 %), as the inertia parameter of segment 1 (2) increases from 0 to 2. This implies that as the level of inertia in either segment increases, the investing incentive becomes more important for both cola manufacturers.

As far as the retail prices are concerned, in Figure 2.4, Coke's (Pepsi's) retail price decreases from \$0.79 (\$0.75) to \$0.76 (\$0.70), i.e., 4 % (7 %) as the inertia parameter of segment 2 increases from 0 to 2. This corresponds to a decrease in retail profit margin of 1.5 % (9 %). This can be compared to the corresponding decrease in wholesale profit margin for Coke (Pepsi)

of 20 % (16 %). This implies that as the level of inertia in segment 2 increases, the investing incentive becomes more important for the retailer, although it is still less than the investing incentives for the manufacturers. At high levels of inertia, the manufacturers and the retailer both bear significant costs of investing, although the retailer disproportionately draws, when compared to the manufacturers, from the additional profits that accrue to the channel (as evidenced by the profit curves of Figure 2.5).

In Figure 2.3, as the inertia parameter of segment 1 increases from 0 to 2, Coke's retail price decreases from \$0.79 to \$0.78, but Pepsi's retail price *increases* from \$0.70 to \$0.75. However, since these decreases are shallower than the corresponding decreases in wholesale prices, the retail profit margins of both Coke and Pepsi increase over that range, by 19 % and 35 %, respectively. In other words, as the level of inertia in segment 1 increases, while the manufacturers bear increasingly higher costs of investing by lowering their wholesale profit margins, the retailer not only does not entirely pass through the wholesale price decreases to end consumers but also enjoys increasing retail profit margins at higher levels of inertia. This is the ultimate free ride for the retailer at the expense of the cola manufacturers.

The steady-state demands for both brands that correspond to the retail prices reflected in Figure 2.3 and 2.4 are found to steadily increase as the inertia parameter of the respective segment increases. In order to see how the steady-state demand within each segment behaves, we separately plot the steady-state demand from each segment in Figures 2.5 and 2.6. All the demand curves are monotonically increasing with the level of inertia, except the demand curve for Pepsi in segment 2 in Figure 2.5, which is monotonically decreasing with the level of inertia of segment 1. This can be easily understood by the fact that the corresponding retail price curve for Pepsi in Figure 2.3 is upward sloping. As price increases, demand must decrease. In segment

1, on the other hand, the adverse impact of increasing retail price of Pepsi is overwhelmed by the increase in the level of inertia of segment 1, which leads to a net impact of increasing inertia that is still positive.

2.6.2 Counterfactual Simulation 2: Behavioral Price Discrimination

Since there are two consumer segments in the cola market under study, each with a different level of inertia and price sensitivity, a question that arises pertains to whether the channel members can improve their profits from employing behavioral price discrimination where customized price-off coupons are mailed to consumers belonging to the more price-sensitive segment (in our case, segment 2). A related question that arises pertains to which channel members must employ such price-off couponing strategies. We conduct a counterfactual simulation to answer these questions. The results of this simulation are summarized in Table 2.4.

First, we simulate the channel members' profits under the assumption that the same price is offered to both consumer segments. The simulated profits under this assumption (called "Scenario 1") are reported in the second column of Table 2.4. Second, we simulate the channel members' profits under the assumption that the retailer mails customized coupons to customers belonging to segment 2.²⁸ The simulated profits under this assumption (called "Scenario 2") are reported in the third column of Table 2.4. All channel members seem to benefit from the retailer's ability to offer different retail prices to the two consumer segments. The profits of Coke, Pepsi and the retailer improve by 1 %, 7 % and 4 %, respectively (with the channel profit improving by 4 %). Third, we simulate the channel members' profits under the assumption that the manufacturers, as opposed to the retailer, mail customized coupons to customers belonging to

²⁸ The retailer can analyze its customer database, which is constructed by tracking the purchase transactions of its customers using their loyalty card, to infer which customer belongs to segment 2.

segment 2.²⁹ The simulated profits under this assumption (called “Scenario 3”) are reported in the fourth column of Table 2.4. The profit of each manufacturer increases by 5 %, while the profit of the retailer decreases by 0.5 %, going from Scenario 2 to Scenario 3 (with the channel profit increasing by 2 %). However, the retailer can fully extract the surplus profit of both manufacturers under Scenario 3, relative to Scenario 2, by charging for its customer database. Once we account for this, we find that the retailer will be better off under Scenario 3 than under Scenario 2 (with a profit increase of 3 %), while keeping the manufacturers indifferent between the scenarios. In other words, the retailer is better off selling its customer database to the manufacturers and letting them offer customized coupons to customers in segment 2, than undertaking such customization itself. Additionally, in order to study whether the retailer may prefer sharing its customer database with only one manufacturer, we simulate the channel members’ profits under the assumption that only one manufacturer, as opposed to both as in Scenario 3, mails customized coupons to customers belonging to segment 2.³⁰ The simulated profits under this assumption (which yield “Scenario 4” and “Scenario 5”) are reported in the fifth and sixth columns of Table 2.4. We find that while sharing the customer data with Pepsi (but not Coke), and fully extracting Pepsi’s additional surplus by charging for the data, makes the retailer better off compared to Scenario 2. However, it is still dominated by Scenario 3. In other words, the retailer’s best option is to charge both manufacturers for use of its customer database and then let them drop customized coupons to customers belonging to segment 2. This finding is qualitatively consistent with the findings in Pancras and Sudhir (2007), although they use a myopic pricing model in their study.

²⁹ The retailer must share its customer database with the cola manufacturers in order to facilitate this.

³⁰ The retailer must share its customer database with the cola manufacturers in order to facilitate this.

As far as what the retailer can charge the manufacturers for using its customer database, the retailer can extract the additional surplus that Coke obtains under Scenario 3 relative to Scenario 5 (when only Pepsi drops customized coupons), as well as extract the additional surplus that Pepsi obtains under Scenario 3 relative to Scenario 4 (when only Coke drops customized coupons). In other words, the retailer can charge \$0.013 ($= \$0.212 - \0.199) to Coke and \$0.062 ($= \$0.563 - \0.501) to Pepsi in order to let them use its customer database. Interestingly, this yields a net profit of \$1.087 ($= \$1.012 + \$0.013 + \0.062) to the retailer, while yielding net profits to Coke and Pepsi of \$0.199 and \$0.501, respectively, which are both lower than their profit counterparts under Scenario 1 (\$0.200 and \$0.503). In other words, the retailer not only benefits from inducing manufacturers to behaviorally price discriminate between the two consumer segments by dropping customized coupons to segment 2 (which yields a profit improvement of 7 % to the retailer relative to Scenario 2, where the retailer drops the customized coupons itself) but ends up making the manufacturers slightly worse off than under the case of no price discrimination! This is in contrast to the situation in Pancras and Sudhir (2007), where the authors find that the manufacturers' profits improve, relative to the case of no price discrimination, along with the retailer's profit.

2.7 Conclusions

In this study, we propose and estimate, for the first time in the literature, a structural pricing model for the distribution channel in the presence of inertial demand. For this purpose, we study the cola market, which is characterized by significant inertia in consumers' brand choices over time. We estimate a consumer-level brand choice model, which includes the effects of inertia, using *scanner panel data* on cola brand choices of consumers in a local market over a period of two years. We then estimate a structural econometric pricing model, that accounts for the pricing interactions, both among manufacturers, as well as between each manufacturer and the retailer, using *retail tracking data* on store-level prices of cola brands from the same local market over the same period of two years. Using a two-segment brand choice model, we find that the cola category is characterized by significant inertia in demand, with estimated brand-level switching costs of \$0.30 and \$0.13 for the two consumer segments.

The net impact of the harvesting and investing incentives for cola manufacturers in our data is that the equilibrium wholesale prices of both brands are *lower* (by 11.9 % and 7.1 % of costs, for Coke and Pepsi, respectively) than those in the absence of inertia. In other words, the harvesting incentive -- which increases equilibrium wholesale prices of Coke and Pepsi by 5.2 % and 11.3 %, respectively -- is dominated by the investing incentive -- which decreases equilibrium wholesale prices of Coke and Pepsi by 17.1 % and 18.4 %, respectively -- for cola brands. For the retailer, however, while the harvesting incentive increases the retailer's profit margin by 1.9c and 2.5c, the investing incentive has no impact on retail profit margin. In other words, while the retailer exploits the benefit of the harvesting incentive, by appropriately increasing his retail profit margin, almost equally with the manufacturers, the cost of investing is borne entirely by the manufacturers. In other words, the retailer effectively free rides on the

manufacturers' efforts by taking a lion's share of the additional profits that accrue to the channel from the existence of inertial demand. In terms of the net effect of the harvesting and investing incentives on distribution channel profits, we uncover a 3c lowered channel profit margin for Coke, but no change in the channel profit margin for Pepsi.

Using the estimates of our structural econometric model, we study the impact of inertial demand on the estimated profitability of the retailer and each manufacturer using two counterfactual simulations. In the first counterfactual simulation, we study the impact of increasing inertia on each channel member's profits and investigate which player in the distribution channel – manufacturer or retailer -- is in a better position to leverage the benefits of inertial demand in terms of gaining disproportionately more from, say, increasing levels of inertia in the market. We find that all channel members gain from increasing levels of inertia, with the retailer gaining disproportionately more than the manufacturers. The investing incentive becomes more important for manufacturers as the level of inertia in either consumer segment increases, thus leading to lower wholesale profit margins. However, as far as the retailer is concerned, an interesting asymmetry emerges. As the level of inertia in the less inertial segment increases, the investing incentive becomes more important to the retailer, thus leading to lower retail profit margins, although at a slower rate than for the manufacturers. However, as the level of inertia in the more inertial segment increases, the retailer not only does not bear the costs of the investing incentive (while the manufacturers do), but also ends up free-riding on the manufacturers' efforts by steadily increasing his retail profit margins on both brands. This simulation suggests that the retailer is in a more leveraged position of strength when it comes to exploiting the increase in inertial demand for cola brands in either consumer segment.

In the second counterfactual simulation, we study the benefits of behavioral price discrimination, using price-off coupons that are customized across behavioral segments of consumers, for the retailer and the manufacturers. We find that the retailer can improve retail profit by 4 % by dropping customized coupons to customers belonging to the more price-sensitive / less inertial segment. Interestingly, we find that the retailer can improve retail profit by an additional 7 % by selling its customer database to both cola manufacturers and letting them drop customized coupons for their brands to customers belonging to segment 2, as opposed to dropping the customized coupons itself. In other words, facilitating manufacturer couponing is a more profitable strategy to the retailer than undertaking store couponing itself. Interestingly, this leads to both manufacturers being slightly worse off, in terms of reduced wholesale profits, when compared to the case of no price discrimination. In other words, the retailer not only entirely benefits at the expense of manufacturers, but also induces the manufacturers to invest the necessary effort to generate the additional channel profits.

Some caveats are in order. First, we treat prices as exogenous in our demand model, i.e., we do not allow for unobserved demand shocks. We acknowledge that our estimates of marginal costs may, therefore, be over-estimated if such unobserved demand shocks exist (see Che, Sudhir and Seetharaman 2007 for a discussion of this issue). Second, our model does not capture an additional source of dynamics in demand, i.e., due to consumer stockpiling behavior, which has implications for dynamic pricing. In the cola category, however, stockpiling is not pervasive as revealed in our data. Households typically buy their preferred quantity of cola on purchase occasions. Therefore, ignoring the effects of consumer stockpiling may not be a critical omission in our case. That said, while extending our model to product categories where consumer

stockpiling is, in fact, significant, explicitly modeling stockpiling behavior, as well as its implications for dynamic pricing, would be necessary.

2.8 Technical Appendices

2.8.1 Appendix 1: Forward Simulation

The objective of this simulation exercise is to calculate the continuation values $EV_R(s)$, and $EV_j(s)$, $j=1,2,\dots,J$ in the Bellman equations of the retailer and each manufacturer for a given cost structure (c_j, σ_j) , and policy function parameters $(\beta_{p_j}, \beta_{w_j})$ in the numerical search routine.

We simulate numerous paths. For each simulated path, we first choose (s_0, ν_0) from the state space. We then run the following simulation routine:

1. Given (s_0, ν_0) and the assumed parametric policy functions calculate $p_0(s_0, \nu_0)$ and $w_0(s_0, \nu_0)$. Then, calculate demand $D_0(s_0, p_0)$
2. Given $p_0(s_0, \nu_0)$, $w_0(s_0, \nu_0)$ and $D_0(s_0, p_0)$, calculate $\pi_0^R = \sum_j (p_{0j} - w_{0j}) D_{0j}$ and $\pi_0^j = (w_{0j} - c_j - \nu_{0j}) D_{0j}$, $j=1,2,\dots,J$. Then calculate installed customer base in the next period $s_1(s_0, p_0)$.
3. Given s_1 , draw ν_1 . Given (s_1, ν_1) repeat steps 1,2.
4. Repeat step 3 for T times until that $\beta^T \approx 0$.

Taking discounted sum of profits calculated for each of the T periods, and averaging over all simulation paths gives us the set of approximated values for each channel member $V_R(s_0, \nu_0)$, and $V_j(s_0, \nu_0)$, $j=1,2,\dots,J$. We then regress these values on (s_0, ν_0) to get approximated value functions for any arbitrary state variables.

2.8.2 Appendix 2: Multi-Agent NFXP Algorithms for Counterfactual Studies

2.8.2.1 Dynamic Channel Pricing

In this numerical exercise, each period the retailer chooses two dynamic policies ($p_j, j=1,2$), and each manufacturer is chooses one dynamic policy (Coke chooses w_1 and Pepsi chooses w_2) given the cost structure from the proposed model. Here is the algorithm:

1. Start with $p_1^0, p_2^0, w_1^0, w_2^0$
 - 1.1. Given w_1^0, w_2^0 , get the optimal dynamic response of the retailer by running the subroutine 2.1.2.
 - 1.2. In order to get $\partial p / \partial w_0$, run the subroutine 2.1.3.
 - 1.3. Given $\partial p / \partial w_0$, find w_1^1, w_2^1 as follows
 - 1.3.1. Given w_2^0 , get $w_1^{0,1}$ by running the subroutine 2.1.5.
 - 1.3.2. Given $w_1^{0,1}$, get $w_2^{0,1}$ by running the subroutine 2.1.7.
 - 1.3.3. Repeat 1.3.1-1.3.2 until $\|w^{0,n} - w^{0,n-1}\| \approx 0$.
 - 1.3.4. Set $w^1 = w^{0,n}$
 - 1.4. Repeat 1.1-1.4 until $\|w^n - w^{n-1}\| \approx 0, \|p^n - p^{n-1}\| \approx 0$.
 - 1.5. Set $w^* = w^n, p^* = p^n$

2.8.2.1.1 Subroutine Retailer Optimality

The objective of this subroutine is to find the best response of the retailer p_1^*, p_2^* to a given set of actions of Coke (M1) and Pepsi (M2): w_1, w_2 , under a given expected continuation value in the retailer's Bellman equation $EV_R(s)$. In other words, the objective is given by

$$(p_1, p_2) = \arg \max \{(p_1 - w_1)D_1 + (p_2 - w_2)D_2 + \beta EV_R(s' | s, p)\}$$

where D_j is the demand for product $j=1,2$. In order to find optimal p_1^*, p_2^*

1. Start with p_1^0, p_2^0 . Given p_1^0, p_2^0 calculate the following:

$$\frac{\partial V_R(s, \nu)}{\partial p_1} = D_1 + (p_1 - w_1)D_{11} + (p_2 - w_2)D_{21} + BEV_{R1}(s')$$

$$\frac{\partial V_R(s, \nu)}{\partial p_2} = D_2 + (p_1 - w_1)D_{12} + (p_2 - w_2)D_{22} + BEV_{R2}(s')$$

where $D_{jk} = \partial D_j / \partial p_k, j, k=1,2$, and $EV_{Rj} = (\partial EV_R(s') / \partial s')(\partial s' / \partial p_j), j=1,2$

By rearranging, we can get p_1^1, p_2^1 as follows:

$$p_1^1 = w_1 - [D_1 + (p_2 - w_2)D_{21} + BEV_{R1}(s')][D_{11} + D_{21}]^{-1}$$

$$p_2^1 = w_2 - [D_2 + (p_1 - w_1)D_{12} + BEV_{R2}(s')][D_{12} + D_{22}]^{-1}$$

2. Given p_1^1, p_2^1 , repeat step 1, to get p_1^2, p_2^2
3. Repeat step 2 to update p_1, p_2 until an iteration n such that $\|p^n - p^{n-1}\| \approx 0$
4. Set $p_1^* = p_1^n, p_2^* = p_2^n$

2.8.2.1.2 Subroutine Dynamic Retailer Response

The objective of this subroutine is to find the dynamic best response of the retailer to the actions of M1 and M2: w_1, w_2 . Here is how it goes:

1. Start with $EV_R^0(s) = 0$: the expected continuation value in the retailer's Bellman equation is zero.
 - a. Get p_1^{0*}, p_2^{0*} under $EV_R^0(s) = 0$ by using the subroutine 2.1.1. Given p_1^{0*}, p_2^{0*} calculate the following Bellman equation over the state space (s, ν)

$$V_R^1(s, \nu) = (p_1^{0*} - w_1)D_1 + (p_2^{0*} - w_2)D_2 + \beta E_\nu V_R(s' | s, p^{0*})$$

Then, calculate $EV_R^1(s)$ by averaging $V_R^1(s, \nu)$ over ν .

- b. Given $EV_R^1(s)$, get p_1^{1*}, p_2^{1*} by using the subroutine 2.1.1. Calculate the Bellman equation in (a) under p_1^{1*}, p_2^{1*} . Update the expected continuation value to $EV_R^2(s)$
- c. Repeat (b) until an iteration n such that $\|p^{n*} - p^{n-1*}\| \approx 0$
- d. Set $p_1^* = p_1^{n*}, p_2^* = p_2^{n*}$

2.8.2.1.3 Subroutine Retailer Best Response

The objective of this subroutine is to find the responses of the retailer to manufacturer's actions, namely $\partial p / \partial w$. In order to do that, we will repeat the subroutine 2.1.2 under the following set of actions of M1, and M2:

$$(w_1 + h, w_2), (w_1, w_2 + h), (w_1 - h, w_2), (w_1, w_2 - h)$$

Then, we can get the related derivatives numerically as follows:

$$\frac{\partial p_j}{\partial w_k} = \lim_{h \rightarrow 0} \frac{p_j^*(w_k + h, w_{-k}) - p_j^*(w_k - h, w_{-k})}{2h}, j, k = 1, 2$$

2.8.2.1.4 Subroutine Coke's Optimality

The objective of this subroutine is to get the optimal response of Coke w_1^* to Pepsi's action w_2 under the retailer's response $\partial p / \partial w$ and the given expected continuation value of Coke $EV_1(s)$.

Here is the subroutine:

1. Start with w_1^0 . Calculate the following Bellman equation

$$V_1(s, \nu) = (w_1 - mc_1 - v_1)D_1 + BEV_1(s' | s, p)$$

where mc_1 is the marginal cost of Coke. If we take the derivative of the above Bellman equation with respect to w_1^0 , we get the following:

$$\frac{\partial V_1(s, v)}{\partial w_1} = D_1 + MR_1 \frac{\partial D_1}{\partial w_1} + \beta \frac{\partial EV_1(s')}{\partial w_1}$$

where

$$MR_1 = (w_1 - mc_1 - v_1)$$

$$\frac{\partial D_1}{\partial w_1} = \frac{\partial D_1}{\partial p_1} \frac{\partial p_1}{\partial w_1} + \frac{\partial D_1}{\partial p_2} \frac{\partial p_2}{\partial w_1}, \quad k = 1, 2$$

$$\frac{\partial EV_1(s')}{\partial w_1} = \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial p_1} \frac{\partial p_1}{\partial w_1} + \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial p_2} \frac{\partial p_2}{\partial w_1}$$

Then, w_1^* becomes

$$w_1^* = MC_1 - \left[D_1 + \beta \frac{\partial EV_1(s')}{\partial w_1} \right] \left[\frac{\partial D_1}{\partial w_1} \right]^{-1}$$

where $MC_1 = mc_1 + v_1$. Then, set $w_1^1 = w_1^*$

2. Repeat (1) with w_1^1 , and from the optimality condition above get w_1^2 .
3. Repeat (2) until an iteration n such that $\|w_1^n - w_1^{n-1}\| \approx 0$.
4. Set $w_1^* = w_1^n$

2.8.2.1.5 Subroutine Dynamic Coke Response

The objective of this subroutine is to find the dynamic best response of Coke w_1 to Pepsi's action w_2 under the retailer's best response $\partial p / \partial w$. Here is the subroutine:

1. Start with $EV_1(s) = 0$: the continuation value in Coke's Bellman equation is zero.

- a. Get w_1^{0*} under $V_1(s) = 0$ by using the subroutine 2.1.4. Calculate Coke's Bellman equation under w_1^{0*} , label the calculated expected continuation value $EV_1^1(s)$.
- b. Given $V_1^1(s)$, get w_1^{1*} by using the subroutine 2.1.4. Calculate Coke's Bellman equation under w_1^{1*} . Label the expected continuation value $EV_1^2(s)$.
- c. Repeat (b) until an iteration n such that $\|w_1^{n*} - w_1^{n-1*}\| \approx 0$
- d. Set $w_1^* = w_1^{n*}$

2.8.2.1.6 Subroutine Pepsi's Optimality

The objective of this subroutine is to get the optimal response of Pepsi w_2 to Coke's action w_1 under the retailer's response $\partial p / \partial w$ and given expected continuation value of Pepsi $EV_2(s)$.

The way this subroutine works is very similar to the subroutine 2.1.4 (see subroutine 2.1.4 for details). Here is the subroutine:

1. Start with w_2^0 . Calculate the following Bellman equation

$$V_2(s, v) = (w_2 - mc_2 - v_2)D_2 + BEV_2(s' | s, p)$$

where mc_2 is the marginal cost of Pepsi. Similar to 2.1.4, we take the derivative of the above Bellman equation with respect to Pepsi's action. Then, we set w_2^1 to the optimal action coming from the first-order condition.

2. Repeat (1) with w_2^1 , and from the optimality conditions, get w_2^2 .
3. Repeat (2) until an iteration n such that $\|w_2^n - w_2^{n-1}\| \approx 0$.
4. Set $w_2^* = w_2^n$

2.8.2.1.7 Subroutine Dynamic Pepsi Response

The objective of this subroutine is to find the dynamic best response of Pepsi w_2 to Coke's action w_1 under the retailer's best response $\partial p / \partial w$. Here is the subroutine:

1. Start with $EV_2(s) = 0$: the continuation value in Pepsi's Bellman equation is zero.
 - a. Get w_2^{0*} under $EV_2(s) = 0$ by using the subroutine 2.1.6. Given w_2^{0*} calculate the Bellman equation of Pepsi, and label the calculated expected continuation value $EV_2^1(s)$.
 - b. Given $EV_2^1(s)$, get w_2^{1*} by using the subroutine 2.1.6. Calculate the Bellman equation of Pepsi under w_2^{1*} . Label the expected continuation value $EV_2^2(s)$.
 - c. Repeat (b) until an iteration n such that $\|w_2^{n*} - w_2^{n-1*}\| \approx 0$
 - d. Set $w_2^* = w_2^{n*}$.

2.8.2.2 Appendix 2.2: Manufacturer Couponing

Here, we illustrate the general case under which both manufacturers send coupons to more (less) price sensitive (inertial) segment. The cases under which only one manufacturer sends the coupon can be studied in a straight-forward manner. In this counterfactual, each period, each agent chooses two dynamic policies given the cost structure from the proposed model: the retailer chooses two retail prices, and each manufacturer chooses a coupon value and a wholesale price. Here is the algorithm:

1. Start with $p_1^0, p_2^0, w_1^0, w_2^0, c_1^0, c_2^0$
 - 1.1. Given $w_1^0, w_2^0, c_1^0, c_2^0$, get the optimal dynamic response of the retailer by running the subroutine 2.2.2.

1.2. In order to get $\partial p / \partial w_0, \partial p / \partial c_0$, run the subroutine 2.2.3.

1.3. Given $\partial p / \partial w_0, \partial p / \partial c_0$, find $w_1^1, w_2^1, c_1^1, c_2^1$ as follows

1.3.1. Given w_2^0, c_2^0 , get $w_1^{0,1}, c_1^{0,1}$ by running the subroutine 2.2.5.

1.3.2. Given $w_1^{0,1}, c_1^{0,1}$, get $w_2^{0,1}, c_2^{0,1}$ by running the subroutine 2.2.7.

1.3.3. Repeat 1.3.1-1.3.2 until $\|w^{0,n} - w^{0,n-1}\| \approx 0, \|c^{0,n} - c^{0,n-1}\| \approx 0$.

1.3.4. Set $w^1 = w^{0,n}, c^1 = c^{0,n}$

1.4. Repeat 1.1-1.4 until $\|w^n - w^{n-1}\| \approx 0, \|c^n - c^{n-1}\| \approx 0, \|p^n - p^{n-1}\| \approx 0$.

1.5. Set $w^* = w^n, c^* = c^n, p^* = p^n$

2.8.2.2.1 Subroutine Retailer Optimality

The objective of this subroutine is to find the best response of the retailer p_1^*, p_2^* to a given set of actions of M1 and M2: w_1, w_2, c_1, c_2 , under the expected continuation value in retailer's Bellman equation $EV_R(s)$. In other words, the objective is given by

$$(p_1, p_2) = \arg \max \{ (p_1 - w_1)(D_{11} + D_{21}) + (p_2 - w_2)(D_{12} + D_{22}) + \beta EV_R(s' | s, p) \}$$

where D_{ij} is the demand from consumer segment $i=1,2$ for product $j=1,2$. In order to find optimal

$$p_1^*, p_2^*$$

1. Start with p_1^0, p_2^0 . Given p_1^0, p_2^0 calculate the following:

$$\frac{\partial V_R(s, v)}{\partial p_1} = D_{11} + D_{21} + (p_1 - w_1)(D_{111} + D_{211}) + (p_2 - w_2)(D_{121} + D_{221}) + BEV_{R1}(s')$$

$$\frac{\partial V_R(s, v)}{\partial p_2} = D_{12} + D_{22} + (p_1 - w_1)(D_{112} + D_{212}) + (p_2 - w_2)(D_{122} + D_{222}) + BEV_{R2}(s')$$

where $D_{ijk} = \partial D_{ij} / \partial p_k$, $i, j, k=1, 2$, and $EV_{R_j} = (\partial EV_R(s') / \partial s')(\partial s' / \partial p_j)$, $j=1, 2$

By rearranging, we can get p_1^1, p_2^1 as follows:

$$p_1^1 = w_1 - [D_{11} + D_{21} + (p_2 - w_2)(D_{121} + D_{221}) + BEV_{R1}(s')] [D_{111} + D_{211}]^{-1}$$

$$p_2^1 = w_2 - [D_{12} + D_{22} + (p_1 - w_1)(D_{112} + D_{212}) + BEV_{R2}(s')] [D_{122} + D_{222}]^{-1}$$

2. Given p_1^1, p_2^1 , repeat step 1, to get p_1^2, p_2^2
3. Repeat step 2 to update p_1, p_2 until an iteration n such that $\|p^n - p^{n-1}\| \approx 0$
4. Set $p_1^* = p_1^n, p_2^* = p_2^n$

2.8.2.2.2 Subroutine Dynamic Retailer Response

The objective of this subroutine is to find the dynamic best response of the retailer to the actions of M1, and M2: w_1, w_2, c_1, c_2 . Here is how it goes:

1. Start with $EV_R^0(s) = 0$: the expected continuation value is in the retailer's Bellman equation is zero.
 - a. Get p_1^{0*}, p_2^{0*} under $EV_R^0(s) = 0$ by using the subroutine 2.2.1. Given p_1^{0*}, p_2^{0*} calculate the following Bellman equation over the state space (s, ν) :
$$V_R^1(s, \nu) = (p_1^{0*} - w_1)(D_{11} + D_{21}) + (p_2^{0*} - w_2)(D_{12} + D_{22}) + \beta E_\nu V_R(s' | s, p^{0*})$$
Calculate $EV_R^1(s)$ by averaging $V_R^1(s, \nu)$ over ν .
 - b. Given $EV_R^1(s)$, get p_1^{1*}, p_2^{1*} by using the subroutine 2.2.1. Calculate the Bellman equation in (a) under p_1^{1*}, p_2^{1*} . Update the expected continuation value to $EV_R^2(s)$
 - c. Repeat (b) until an iteration n such that $\|p^{n*} - p^{n-1*}\| \approx 0$
 - d. Set $p_1^* = p_1^{n*}, p_2^* = p_2^{n*}$

2.8.2.2.3 Subroutine Retailer Best Response

The objective of this subroutine is to find the responses of the retailer to manufacturer's actions, namely $\partial p / \partial w, \partial p / \partial c$. In order to do that, we will repeat the Subroutine 2.2.2 under the following set of actions of M1, and M2:

$$(w_1 + h, w_2, c_1, c_2), (w_1, w_2 + h, c_1, c_2), (w_1, w_2, c_1 + h, c_2), (w_1, w_2, c_1, c_2 + h), \\ (w_1 - h, w_2, c_1, c_2), (w_1, w_2 - h, c_1, c_2), (w_1, w_2, c_1 - h, c_2), (w_1, w_2, c_1, c_2 - h)$$

Then, we can get the related derivatives numerically as follows:

$$\frac{\partial p_j}{\partial w_k} = \lim_{h \rightarrow 0} \frac{p_j^*(w_k + h, w_{-k}, c) - p_j^*(w_k - h, w_{-k}, c)}{2h}, j, k=1, 2 \\ \frac{\partial p_j}{\partial c_k} = \lim_{h \rightarrow 0} \frac{p_j^*(w, c_k + h, c_{-k}) - p_j^*(w, c_k - h, c_{-k})}{2h}$$

2.8.2.2.4 Subroutine Coke's Optimality

The objective of this subroutine is to get the optimal response of Coke w_1^*, c_1^* to Pepsi's actions w_2, c_2 under the retailer's response $\partial p / \partial w, \partial p / \partial c$ and the expected continuation value of Coke $EV_1(s)$. Here is how it goes:

1. Start with w_1^0, c_1^0 . Calculate the following Bellman equation

$$EV_1(s, v) = (w_1 - mc_1 - v_1)D_{11} + (w_1 - mc_1 - c_1 - v_1)D_{21} + BE_v V_1(s' | s, p)$$

where mc_1 is the marginal cost of Coke. If we take the derivative of the above Bellman equation with respect to w_1^0, c_1^0 , we get the following:

$$\frac{\partial V_1(s, v)}{\partial w_1} = D_{11} + D_{21} + MR_1 \frac{\partial D_{11}}{\partial w_1} + (MR_1 - c_1) \frac{\partial D_{21}}{\partial w_1} + \beta \frac{\partial EV_1(s')}{\partial w_1} \\ \frac{\partial V_1(s, v)}{\partial c_1} = -D_{21} + MR_1 \frac{\partial D_{11}}{\partial c_1} + (MR_1 - c_1) \frac{\partial D_{21}}{\partial c_1} + \beta \frac{\partial EV_1(s')}{\partial c_1}$$

where

$$MR_1 = (w_1 - mc_1 - v_1)$$

$$\frac{\partial D_{k1}}{\partial w_1} = \frac{\partial D_{k1}}{\partial p_1} \frac{\partial p_1}{\partial w_1} + \frac{\partial D_{k1}}{\partial p_2} \frac{\partial p_2}{\partial w_1}, \quad k = 1, 2$$

$$\frac{\partial D_{k1}}{\partial c_1} = \frac{\partial D_{k1}}{\partial p_1} \frac{\partial p_1}{\partial c_1} + \frac{\partial D_{k1}}{\partial p_2} \frac{\partial p_2}{\partial c_1} - I\{k = 2\} \frac{\partial D_{k1}}{\partial p_1}, \quad k = 1, 2$$

$$\frac{\partial EV_1(s')}{\partial w_1} = \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial p_1} \frac{\partial p_1}{\partial w_1} + \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial p_2} \frac{\partial p_2}{\partial w_1}$$

$$\frac{\partial EV_1(s')}{\partial c_1} = \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial c_1} + \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial p_1} \frac{\partial p_1}{\partial c_1} + \frac{\partial EV_1(s')}{\partial s'} \frac{\partial s'}{\partial p_2} \frac{\partial p_2}{\partial c_1}$$

Then, w_1^*, c_1^* becomes

$$w_1^* = MC_1 - \left[D_{11} + D_{21} - c_1 \frac{\partial D_{21}}{\partial w_1} + \beta \frac{\partial EV_1(s')}{\partial w_1} \right] \left[\frac{\partial D_{11}}{\partial w_1} + \frac{\partial D_{21}}{\partial w_1} \right]^{-1}$$

$$c_1^* = MR_1 + \left[-D_{21} + MR_1 \frac{\partial D_{11}}{\partial c_1} + \beta \frac{\partial EV_1(s')}{\partial c_1} \right] \left[\frac{\partial D_{21}}{\partial c_1} \right]^{-1}$$

where $MC_1 = mc_1 + v_1$. Then, set $w_1^1 = w_1^*, c_1^1 = c_1^*$

2. Repeat (1) with w_1^1, c_1^1 , and from the optimality condition above get w_1^2, c_1^2 .
3. Repeat (2) until an iteration n such that $\|w_1^n - w_1^{n-1}\| \approx 0, \|c_1^n - c_1^{n-1}\| \approx 0$.
4. Set $w_1^* = w_1^n, c_1^* = c_1^n$

2.8.2.2.5 Subroutine Dynamic Coke Response

The objective of this subroutine is to find the dynamic best response of Coke w_1, c_1 to Pepsi's

actions w_2, c_2 under the retailer's best responses $\partial p / \partial w, \partial p / \partial c$. Here is the subroutine:

1. Start with $EV_1(s) = 0$: the continuation value in Coke's Bellman equation is zero.

- a. Get w_1^{0*}, c_1^{0*} under $EV_1(s) = 0$ by using the subroutine 2.2.4. Calculate Coke's Bellman equation under w_1^{0*}, c_1^{0*} , label the calculated Bellman equation $EV_1^1(s)$.
- b. Given $EV_1^1(s)$, get w_1^{1*}, c_1^{1*} by using the subroutine 2.2.4. Calculate Coke's Bellman equation under w_1^{1*}, c_1^{1*} . Label the expected continuation value $EV_1^2(s)$.
- c. Repeat (b) until an iteration n such that $\|w_1^{n*} - w_1^{n-1*}\| \approx 0, \|c_1^{n*} - c_1^{n-1*}\| \approx 0$
- d. Set $w_1^* = w_1^{n*}, c_1^* = c_1^{n*}$

2.8.2.2.6 Subroutine Pepsi's Optimality

The objective of this subroutine is to get the optimal response of Pepsi w_2, c_2 to Coke's actions w_1, c_1 under the retailer's response $\partial p / \partial w, \partial p / \partial c$ and the expected continuation value of Pepsi $EV_2(s)$. Since the way this subroutine works is very similar to the subroutine 2.2.4 (see subroutine 2.2.4 for details). Here is the subroutine:

1. Start with w_2^0, c_2^0 . Calculate the following Bellman equation

$$V_2(s, v) = (w_2 - mc_2 - v_2)D_{12} + (w_2 - mc_2 - c_2 - v_2)D_{22} + BEV_2(s' | s, p)$$

where mc_2 is the marginal cost of Pepsi. Similar to the subroutine 2.2.4, we take the derivative of the above Bellman equation with respect to Pepsi's actions. Then, we set w_2^1, c_2^1 to the actions coming from the first-order conditions.

2. Repeat (1) with w_2^1, c_2^1 , and from the optimality conditions, get w_2^2, c_2^2 .
3. Repeat (2) until an iteration n such that $\|w_2^n - w_2^{n-1}\| \approx 0, \|c_2^n - c_2^{n-1}\| \approx 0$.
4. Set $w_2^* = w_2^n, c_2^* = c_2^n$

2.8.2.2.7 Subroutine Dynamic Pepsi Response

The objective of this subroutine is to find the dynamic best response of Pepsi w_2, c_2 to Coke's actions w_1, c_1 under the retailer's best responses $\partial p / \partial w, \partial p / \partial c$. Here is the subroutine:

1. Start with $EV_2(s) = 0$: the expected continuation value in Pepsi's Bellman equation is zero.
 - a. Get w_2^{0*}, c_2^{0*} under $EV_2(s) = 0$ by using the subroutine 2.2.6. Given w_2^{0*}, c_2^{0*} calculate the Bellman equation of Pepsi under w_2^{0*}, c_2^{0*} , and label the calculated Bellman equation $EV_2^1(s)$.
 - b. Given $EV_2^1(s)$, get w_2^{1*}, c_2^{1*} by using the subroutine 2.2.6. Calculate the Bellman equation of Pepsi under w_1^{1*}, c_1^{1*} . Label the expected continuation value $EV_2^2(s)$.
 - c. Repeat (b) until an iteration n such that $\|w_2^{n*} - w_2^{n-1*}\| \approx 0, \|c_2^{n*} - c_2^{n-1*}\| \approx 0$ Set
 - d. Set $w_2^* = w_2^{n*}, c_2^* = c_2^{n*}$

2.8.2.3 Retailer Couponing

In this case, each period the retailer sends coupons to more (less) price sensitive (inertial) segment, and each manufacturer decides on their own product's wholesale price. This case is equivalent to the case that retailer is charging two set of retail prices (for Coke and Pepsi) to each of the consumer segments ($p_{ij}, i = 1, 2, j = Coke, Pepsi$). Here is the algorithm:

1. Start with $p_{11}^0, p_{12}^0, p_{21}^0, p_{22}^0, w_1^0, w_2^0$
 - 1.1. Given w_1^0, w_2^0 , get the optimal dynamic response of the retailer by running the subroutine 2.3.2.

1.2. In order to get $\partial p / \partial w_0$, run the subroutine 2.3.3.

1.3. Given $\partial p / \partial w_0$, find w_1^1, w_2^1 as follows

1.3.1. Given w_2^0 , get $w_1^{0,1}$ by running the subroutine 2.3.5.

1.3.2. Given $w_1^{0,1}$, get $w_2^{0,1}$ by running the subroutine 2.3.7.

1.3.3. Repeat 1.3.1-1.3.2 until $\|w^{0,n} - w^{0,n-1}\| \approx 0$.

1.3.4. Set $w^1 = w^{0,n}$

1.4. Repeat 1.1-1.4 until $\|w^n - w^{n-1}\| \approx 0, \|p^n - p^{n-1}\| \approx 0$.

1.5. Set $w^* = w^n, p^* = p^n$

2.8.2.3.1 Subroutine Retailer Optimality

The objective of this subroutine is to find the best response of the retailer $p_{11}^*, p_{12}^*, p_{21}^*, p_{22}^*$ to a given set of actions of M1 and M2: w_1, w_2 , under the expected continuation value in retailer's Bellman equation $EV_R(s)$. In other words, the objective is given by

$$(p_{11}, p_{12}, p_{21}, p_{22}) = \arg \max \left\{ \begin{array}{l} (p_{11} - w_1)D_{11} + (p_{21} - w_1)D_{21} + (p_{12} - w_2)D_{12} + (p_{22} - w_2)D_{22} \\ + \beta EV_R(s' | s, p) \end{array} \right\}$$

where D_{ij} is the demand from consumer segment $i=1,2$ for product $j=1,2$. In order to find optimal

$$p_{11}^*, p_{12}^*, p_{21}^*, p_{22}^*$$

1. Start with $p_{11}^0, p_{12}^0, p_{21}^0, p_{22}^0$. Given $p_{11}^0, p_{12}^0, p_{21}^0, p_{22}^0$ calculate the following:

$$\partial V_R(s, v) / \partial p_{11} = D_{11} + (p_{11} - w_1)D_{111} + (p_{12} - w_2)D_{121} + \beta EV_{R11}(s' | s, p)$$

$$\partial V_R(s, v) / \partial p_{12} = D_{12} + (p_{11} - w_1)D_{112} + (p_{12} - w_2)D_{122} + \beta EV_{R12}(s' | s, p)$$

$$\partial V_R(s, v) / \partial p_{21} = D_{21} + (p_{21} - w_1)D_{211} + (p_{22} - w_2)D_{221} + \beta EV_{R21}(s' | s, p)$$

$$\partial V_R(s, v) / \partial p_{22} = D_{22} + (p_{21} - w_1)D_{212} + (p_{22} - w_2)D_{222} + \beta EV_{R22}(s' | s, p)$$

where $D_{ijk} = \partial D_{ij} / \partial p_{ik}$, $i, j, k=1, 2$, and $EV_{Rij} = (\partial EV_R(s') / \partial s')(\partial s' / \partial p_{ij})$, $i, j=1, 2$

By rearranging, we can get $p_{11}^1, p_{12}^1, p_{21}^1, p_{22}^1$ as follows:

$$p_{11}^1 = w_1 + [D_{11} + (p_{12} - w_2)D_{121} + \beta EV_{R11}(s' | s, p)]D_{111}^{-1}$$

$$p_{12}^1 = w_2 + [D_{12} + (p_{11} - w_1)D_{112} + \beta EV_{R12}(s' | s, p)]D_{122}^{-1}$$

$$p_{21}^1 = w_1 + [D_{21} + (p_{22} - w_2)D_{221} + \beta EV_{R21}(s' | s, p)]D_{211}^{-1}$$

$$p_{22}^1 = w_2 + [D_{22} + (p_{21} - w_1)D_{212} + \beta EV_{R22}(s' | s, p)]D_{222}^{-1}$$

2. Given $p_{11}^1, p_{12}^1, p_{21}^1, p_{22}^1$, repeat step 1, to get $p_{11}^2, p_{12}^2, p_{21}^2, p_{22}^2$
3. Repeat step 2 to update $p_{11}, p_{12}, p_{21}, p_{22}$ until an iteration n such that $\|p^n - p^{n-1}\| \approx 0$
4. Set $p_{11}^* = p_{11}^n, p_{12}^* = p_{12}^n, p_{21}^* = p_{21}^n, p_{22}^* = p_{22}^n$

2.8.2.3.2 Subroutine Dynamic Retailer Response

The objective of this subroutine is to find the dynamic best response of the retailer to the actions of M1, and M2: w_1, w_2 . Here is the subroutine:

1. Start with $EV_R^0(s) = 0$: the expected continuation value is in the retailer's Bellman equation is zero.

- a. Get $p_{11}^{0*}, p_{12}^{0*}, p_{21}^{0*}, p_{22}^{0*}$ under $EV_R^0(s) = 0$ by using the subroutine 2.3.1. Given

$p_{11}^{0*}, p_{12}^{0*}, p_{21}^{0*}, p_{22}^{0*}$ calculate the following Bellman equation over the state space (s, v) :

$$V_R^1(s, v) = (p_{11}^{0*} - w_1)D_{11} + (p_{21}^{0*} - w_1)D_{21} + (p_{12}^{0*} - w_2)D_{12} + (p_{22}^{0*} - w_2)D_{22} + \beta EV_R^0(s' | s, p^{0*})$$

Again, calculate $EV_R^1(s)$ by averaging $V_R^1(s, v)$ over v .

- b. Given $EV_R^1(s)$, get $p_{11}^{1*}, p_{12}^{1*}, p_{21}^{1*}, p_{22}^{1*}$ by using the subroutine 2.3.1. Calculate the Bellman equation in (a) under $p_{11}^{1*}, p_{12}^{1*}, p_{21}^{1*}, p_{22}^{1*}$. Update the expected continuation value to $EV_R^2(s)$.
- c. Repeat (b) until an iteration n such that $\|p^{n*} - p^{n-1*}\| \approx 0$
- d. Set $p_{11}^* = p_{11}^{n*}, p_{12}^* = p_{12}^{n*}, p_{21}^* = p_{21}^{n*}, p_{22}^* = p_{22}^{n*}$

2.8.2.3.3 Subroutine Retailer Best Response

The objective of this subroutine is to find the responses of the retailer to manufacturer's actions, namely $\partial p / \partial w$. In order to do that, we will repeat the Subroutine 2.3.2 under the following set of actions of M1, and M2:

$$(w_1 + h, w_2), (w_1, w_2 + h), (w_1 - h, w_2), (w_1, w_2 - h)$$

Then, we can get the related derivatives numerically as follows:

$$\frac{\partial p_{ij}}{\partial w_k} = \lim_{h \rightarrow 0} \frac{p_{ij}^*(w_k + h, w_{-k}) - p_{ij}^*(w_k - h, w_{-k})}{2h} \quad i, j, k = 1, 2$$

2.8.2.3.4 Subroutine Coke's Optimality

The objective of this subroutine is to get the optimal response of Coke w_1^* to Pepsi's action w_2 under the retailer's response $\partial p / \partial w$ and the expected continuation value of Coke $EV_1(s)$. Here is how it goes:

1. Start with w_1^0 . Calculate the following Bellman equation

$$V_1(s, v) = (w_1 - mc_1 - v_1)(D_{11} + D_{21}) + BEV_1(s' | s, p)$$

where mc_1 is the marginal cost of Coke. If we take the derivative of the above Bellman equation with respect to w_1^0 , we get the following:

$$\frac{\partial V_1(s, v)}{\partial w_1} = D_{11} + D_{21} + MR_1 \left(\frac{\partial D_{11}}{\partial w_1} + \frac{\partial D_{21}}{\partial w_1} \right) + \beta \frac{\partial EV_1(s')}{\partial w_1}$$

where

$$MR_1 = (w_1 - mc_1 - v_1)$$

$$\frac{\partial D_{k1}}{\partial w_1} = \frac{\partial D_{k1}}{\partial p_{k1}} \frac{\partial p_{k1}}{\partial w_1} + \frac{\partial D_{k1}}{\partial p_{k2}} \frac{\partial p_{k2}}{\partial w_1}, \quad k = 1, 2$$

$$\frac{\partial EV_1(s')}{\partial w_1} = \frac{\partial EV_1(s')}{\partial s'} \left(\frac{\partial s'}{\partial p_{11}} \frac{\partial p_{11}}{\partial w_1} + \frac{\partial s'}{\partial p_{12}} \frac{\partial p_{12}}{\partial w_1} + \frac{\partial s'}{\partial p_{21}} \frac{\partial p_{21}}{\partial w_1} + \frac{\partial s'}{\partial p_{22}} \frac{\partial p_{22}}{\partial w_1} \right)$$

Then, w_1^* becomes

$$w_1^* = mc_1 + v_1 - \left[D_{11} + D_{21} + \beta \frac{\partial EV_1(s')}{\partial w_1} \right] \left[\frac{\partial D_{11}}{\partial w_1} + \frac{\partial D_{21}}{\partial w_1} \right]^{-1}$$

Then, set $w_1^1 = w_1^*$

2. Repeat (1) with w_1^1 , and from the optimality condition above get w_1^2 .
3. Repeat (2) until an iteration n such that $\|w_1^n - w_1^{n-1}\| \approx 0$.
4. Set $w_1^* = w_1^n$

2.8.2.3.5 Subroutine Dynamic Coke Response

The objective of this subroutine is to find the dynamic best response of Coke w_1 to Pepsi's action w_2 under the retailer's best response $\partial p / \partial w$. Here is the subroutine:

1. Start with $EV_1(s) = 0$: the expected continuation value in Coke's Bellman equation is zero.

- a. Get w_1^{0*} under $EV_1(s) = 0$ by using the subroutine 2.3.4. Calculate Coke's Bellman equation under w_1^{0*} , label the calculated Bellman equation $EV_1^1(s)$.
- b. Given $EV_1^1(s)$, get w_1^{1*} by using the subroutine 2.3.4. Calculate Coke's Bellman equation under w_1^{1*} . Label the expected continuation value $EV_1^2(s)$.
- c. Repeat (b) until an iteration n such that $\|w_1^{n*} - w_1^{n-1*}\| \approx 0$
- d. Set $w_1^* = w_1^{n*}$

2.8.2.3.6 Subroutine Pepsi's Optimality

The objective of this subroutine is to get the optimal response of Pepsi w_2 to Coke's action w_1 under the retailer's response $\partial p / \partial w$ and the expected continuation value of Pepsi $V_2(s)$. Since the way this subroutine works is very similar to the subroutine 2.3.4 (see subroutine 2.3.4 for details). Here is the subroutine:

1. Start with w_2^0 . Calculate the following Bellman equation

$$V_2(s, v) = (w_2 - mc_2 - v_2)(D_{12} + D_{22}) + BEV_2(s' | s, p)$$

where mc_2 is the marginal cost of Pepsi. Similar to the subroutine 2.3.4, we take the derivative of the above Bellman equation with respect to Pepsi's actions. Then, we set w_2^1 to the actions coming from the first-order conditions.

2. Repeat (1) with w_2^1 , and from the optimality conditions, get w_2^2 .
3. Repeat (2) until an iteration n such that $\|w_2^n - w_2^{n-1}\| \approx 0$.
4. Set $w_2^* = w_2^n$

2.8.2.3.7 Subroutine Dynamic Pepsi Response

The objective of this subroutine is to find the dynamic best response of Pepsi w_2 to Coke's action w_1 under the retailer's best response $\partial p / \partial w$. Here is the subroutine:

1. Start with $EV_2(s) = 0$: the expected continuation value in Pepsi's Bellman equation is zero.
 - a. Get w_2^{0*} under $EV_2(s) = 0$ by using the subroutine 2.3.6. Given w_2^{0*} calculate the Bellman equation of Pepsi under w_2^{0*} , and label the calculated Bellman equation $EV_2^1(s)$.
 - b. Given $EV_2^1(s)$, get w_2^{1*} by using the subroutine 2.3.6. Calculate the Bellman equation of Pepsi under w_2^{1*} . Label the expected continuation value $EV_2^2(s)$.
 - c. Repeat (b) until an iteration n such that $\|w_2^{n*} - w_2^{n-1*}\| \approx 0$

Set $w_2^* = w_2^{n*}$

2.8.3 Appendix 3: Monte Carlo Simulations to Test Our Proposed Algorithm

MONOPOLIST MANUFACTURER

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
C_{True}	0.50	0.45	0.55	0.60
C_{Est}	0.500 (0.003)	0.449 (0.002)	0.551 (0.004)	0.599 (0.001)
V_{True}	0.04	0.03	0.05	0.02
V_{Est}	0.0401 (0.003)	0.0314 (0.003)	0.0500 (0.002)	0.0205 (0.001)

MANUFACTURER DUOPOLY

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
$C_{True,Coke}$	0.60	0.50	0.55	0.60
$C_{Est,Coke}$	0.5996 (0.0013)	0.4966 (0.0012)	0.5483 (0.0011)	0.5980 (0.0015)
$C_{True,Pepsi}$	0.55	0.45	0.45	0.50
$C_{Est,Pepsi}$	0.5510 (0.0007)	0.4500 (0.0010)	0.4490 (0.0012)	0.4981 (0.0016)
$V_{True,Coke}$	0.05	0.04	0.03	0.05
$V_{Est,Coke}$	0.0480 (0.0012)	0.0384 (0.0009)	0.0292 (0.0006)	0.0475 (0.0011)
$V_{True,Pepsi}$	0.02	0.03	0.04	0.05
$V_{Est,Pepsi}$	0.0192 (0.0004)	0.0290 (0.0006)	0.0386 (0.0009)	0.0479 (0.0010)

MONOPOLIST MANUFACTURER WITH RETAILER

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
C_{True}	0.55	0.6	0.45	0.5
C_{Est}	0.550 (0.001)	0.600 (0.001)	0.448 (0.002)	0.499 (0.001)
V_{True}	0.04	0.02	0.06	0.03
V_{Est}	0.0389 (0.001)	0.0197 (0.001)	0.0577 (0.001)	0.0298 (0.001)

MANUFACTURER DUOPOLY WITH RETAILER

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
$C_{True,Coke}$	0.55	0.60	0.50	0.55
$C_{Est,Coke}$	0.5473 (0.0014)	0.5995 (0.0017)	0.499 (0.0008)	0.5473 (0.0013)
$C_{True,Pepsi}$	0.5	0.55	0.5	0.55
$C_{Est,Pepsi}$	0.5024 (0.001)	0.5509 (0.0008)	0.4976 (0.0015)	0.5498 (0.0011)

$V_{True,Coke}$	0.04	0.05	0.02	0.03
$V_{Est,Coke}$	0.038 (0.0006)	0.0492 (0.0007)	0.0196 (0.0004)	0.0295 (0.0004)
$V_{True,Pepsi}$	0.04	0.03	0.05	0.04
$V_{Est,Pepsi}$	0.0389 (0.0006)	0.0298 (0.0004)	0.0491 (0.0008)	0.0378 (0.0008)

Table 2.1: Estimation Results – Distribution Channel Pricing Model

Parameter	Estimate
C_{Coke}	\$0.436 (\$0.025)
C_{Pepsi}	\$0.355 (\$0.028)
σ_{Coke}	\$0.059 (\$0.016)
σ_{Pepsi}	\$0.073 (\$0.012)

Table 2.2: Equilibrium Profit Margins

	Dynamic	Myopic	Static
R_{Coke}	\$0.2139 (0.011)	\$0.2128 (0.013)	\$0.1939 (0.009)
R_{Pepsi}	\$0.2151 (0.013)	\$0.2163 (0.014)	\$0.1909 (0.009)
M_{Coke}	\$0.1322 (0.012)	\$0.2066 (0.014)	\$0.1839 (0.008)
M_{Pepsi}	\$0.1641 (0.014)	\$0.2293 (0.018)	\$0.1894 (0.009)

Table 2.3: Manufacturers' Incentives with and without the Retailer

		Investing (Myopic vs. Dynamic)	Harvesting (Static vs. Myopic)
With the Retailer	Coke	-36.0%	12.3%
	Pepsi	-28.4%	21.1%
Without the Retailer	Coke	-24.0%	13.8%
	Pepsi	-20.6%	23.3%

Table 2.4: Counterfactual Simulation on Behavioral Price Discrimination

Scenario 1: No Coupons

Scenario 2: Retailer Drops Coupons

Scenario 3: Both Manufacturers Drop Coupons

Scenario 4: Coke Drops Coupons

Scenario 5: Pepsi Drops Coupons

	Scenario 1: None	Scenario 2: Retailer	Scenario 3: Coke & Pepsi	Scenario 4: Coke	Scenario 5: Pepsi
Retailer Profit	\$0.981	\$1.018	\$1.012	\$0.955	\$0.997
Coke Profit	\$0.200	\$0.202	\$0.212	\$0.221	\$0.199
Pepsi Profit	\$0.503	\$0.536	\$0.563	\$0.501	\$0.572
Channel Profit	\$1.684	\$1.756	\$1.786	\$1.676	\$1.768
P_{Coke}	\$0.782	\$0.803	\$0.794	\$0.792	\$0.794
Coupon _{Coke} ³¹	-	\$0.081	\$0.056	\$0.046	-
P_{Pepsi}	\$0.734	\$0.751	\$0.750	\$0.739	\$0.751
Coupon _{Pepsi} ³²	-	\$0.085	\$0.105	-	\$0.103
W_{Coke}	\$0.568	\$0.566	\$0.587	\$0.590	\$0.576
W_{Pepsi}	\$0.519	\$0.515	\$0.554	\$0.523	\$0.555

**CHANNEL MEMBER PROFITS UNDER THE CASE OF INFORMATION SELLING BY RETAILER TO MANUFACTURERS
(UNDER SCENARIO 3)**

$$\text{RETAILER PROFIT} = \$1.012 + (\$0.212 - \$0.199) + (\$0.563 - \$0.501) = \$1.087$$

$$\text{COKE PROFIT} = \$0.212 - (\$0.212 - \$0.199) = \$0.199$$

$$\text{PEPSI PROFIT} = \$0.563 - (\$0.563 - \$0.501) = \$0.501$$

$$\text{TOTAL CHANNEL PROFIT} = \$1.087 + \$0.199 + \$0.501 = \$1.787$$

³¹ A price-off coupon for Coke for this value is mailed to each consumer in segment 2.

³² A price-off coupon for Pepsi for this value is mailed to each consumer in segment 2.

Figure 2.1: Steady-State Profits as a Function of Segment 1 Inertia

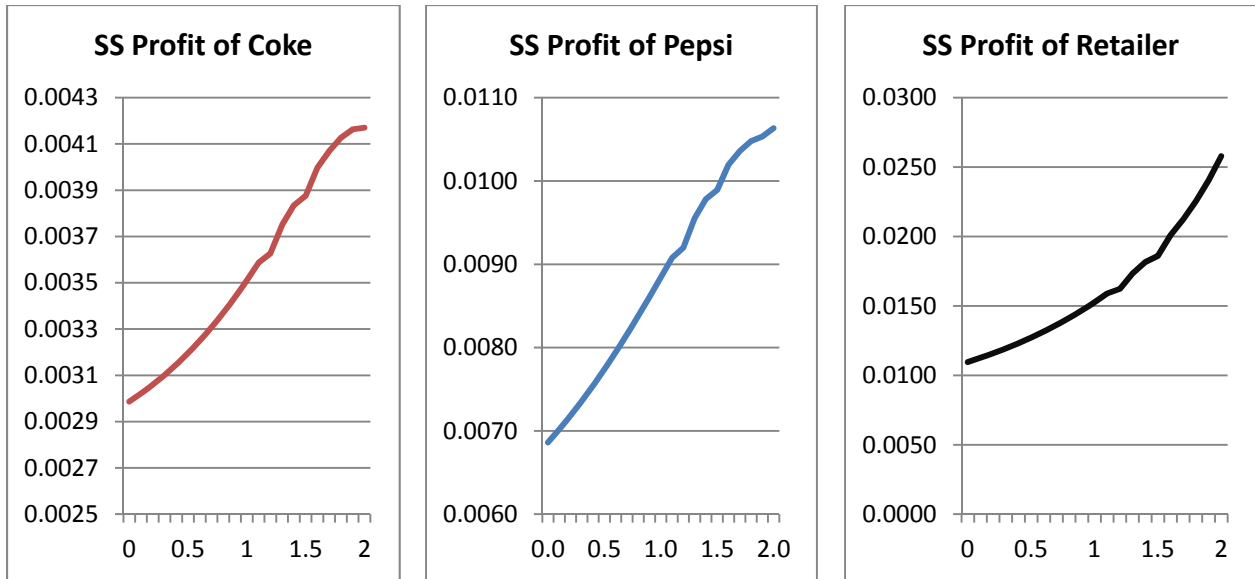


Figure 2.2: Steady-State Profits as a Function of Segment 2 Inertia

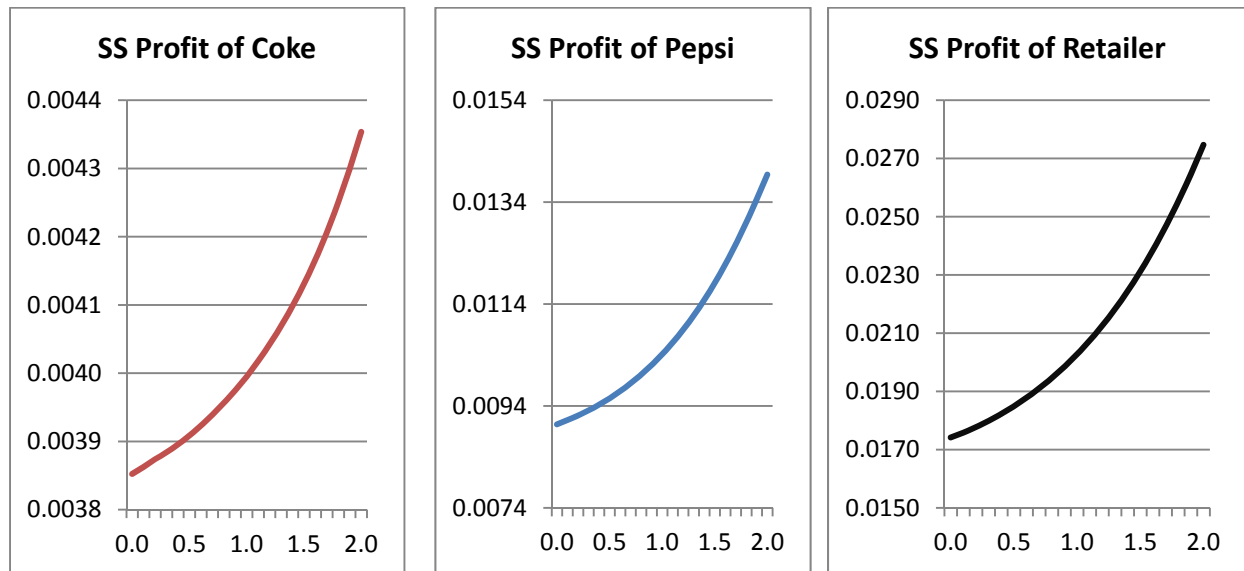


Figure 2.3: Steady-State Prices as a Function of Segment 1 Inertia

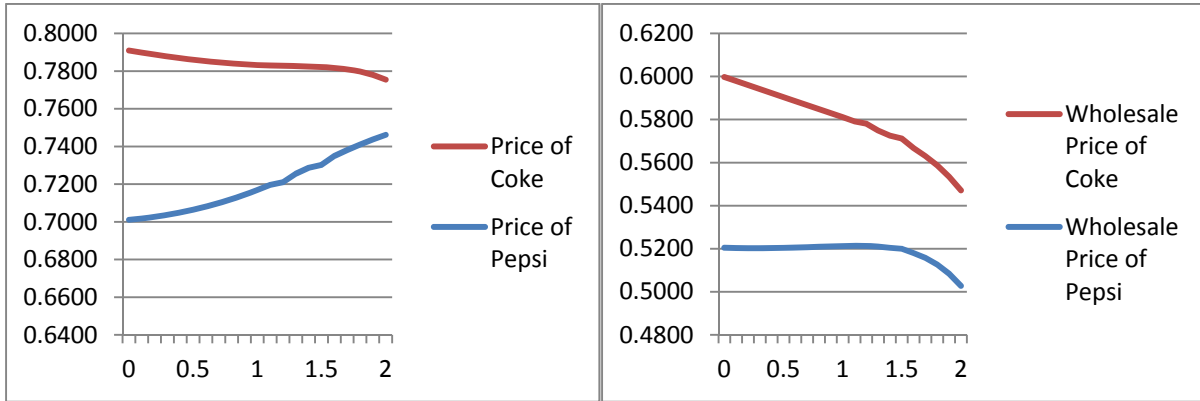


Figure 2.4: Steady-State Prices as a Function of Segment 2 Inertia

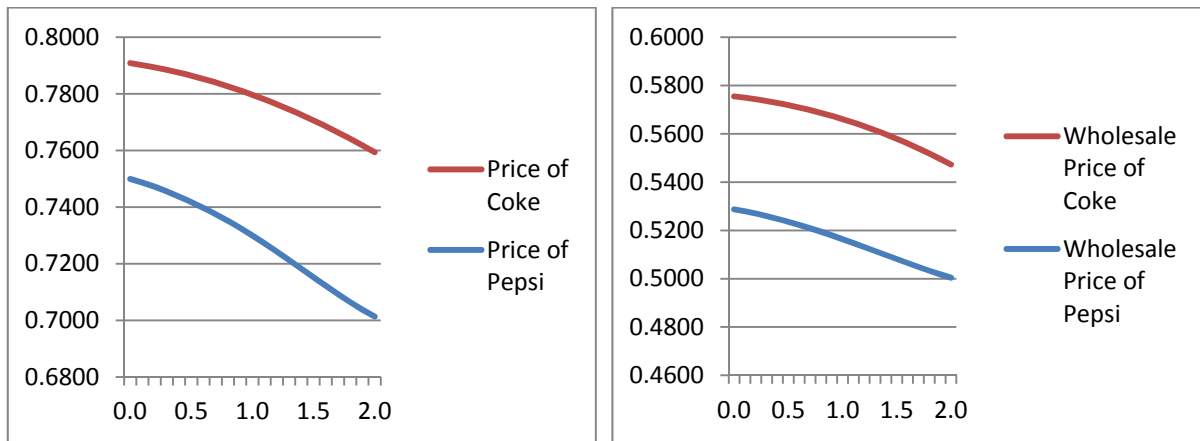


Figure 2.5: Demands as a Function of Segment 1 Inertia

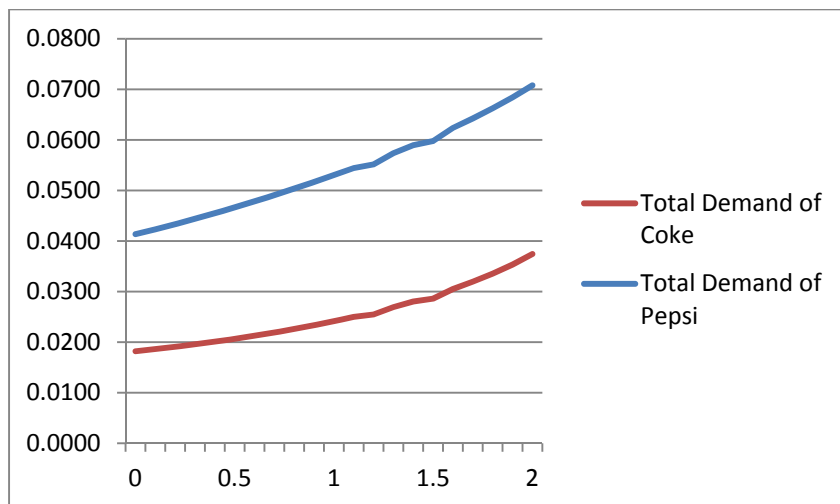
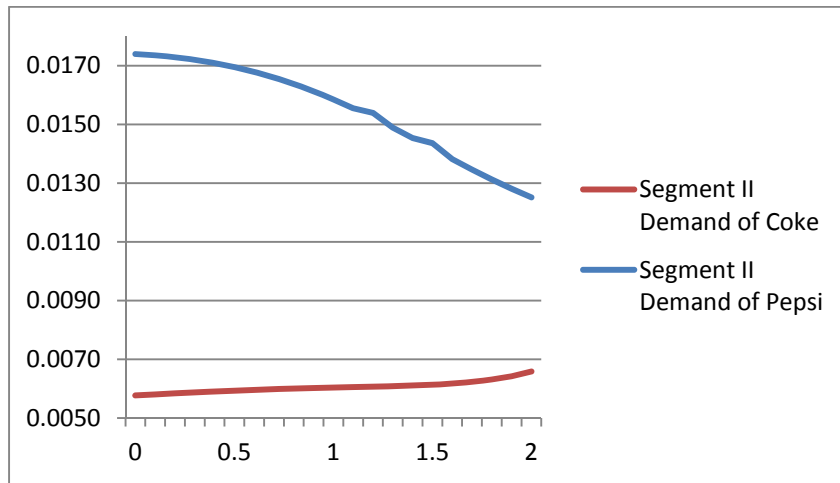
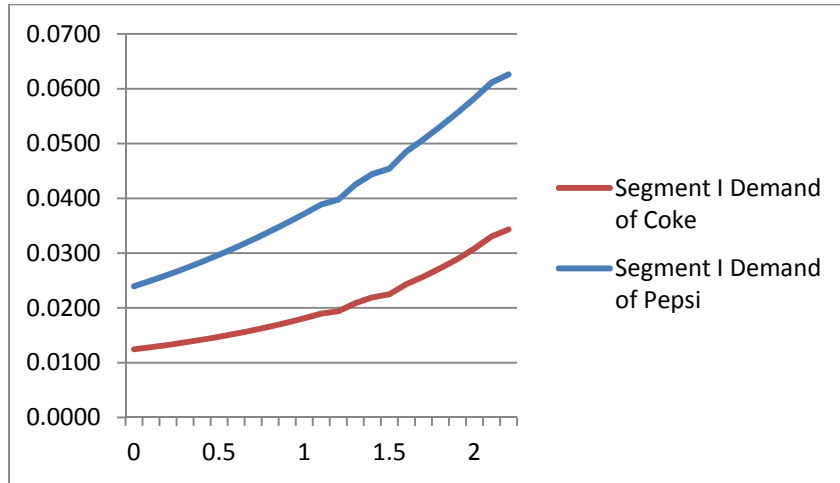
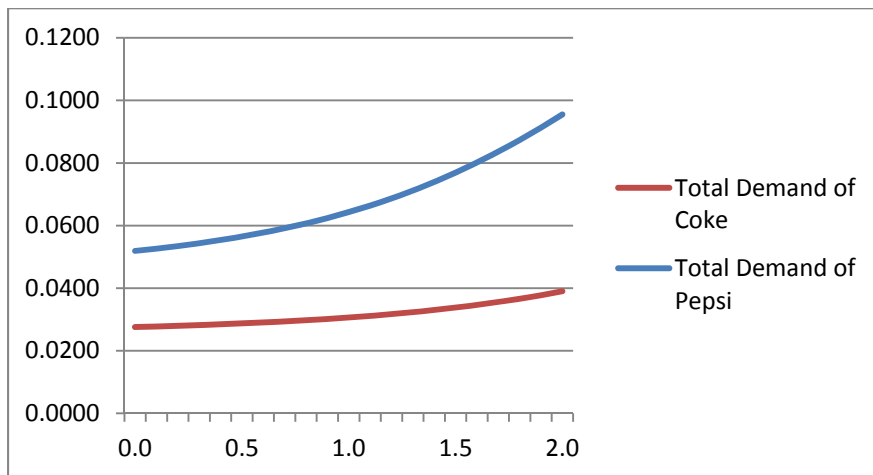
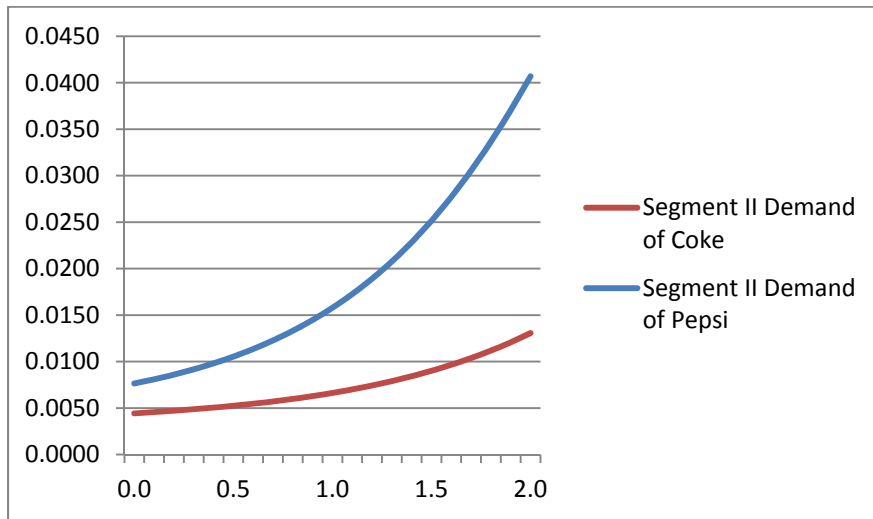
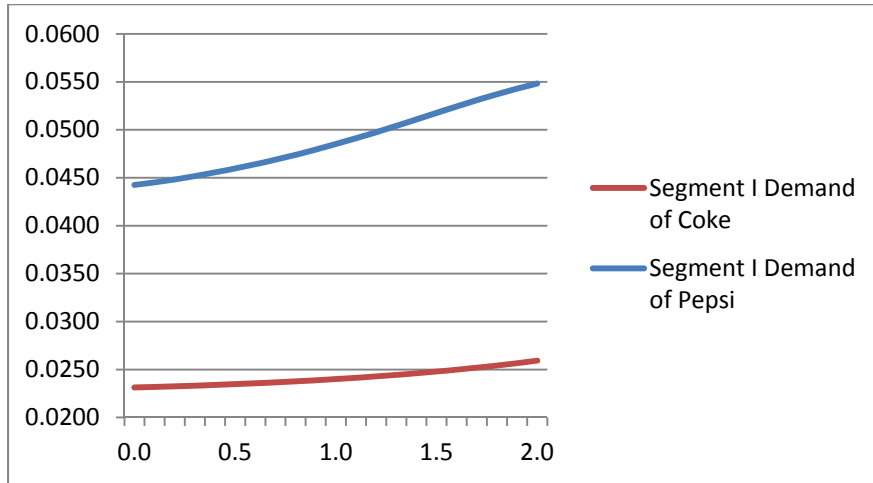


Figure 2.6: Demands as a Function of Segment 2 Inertia



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