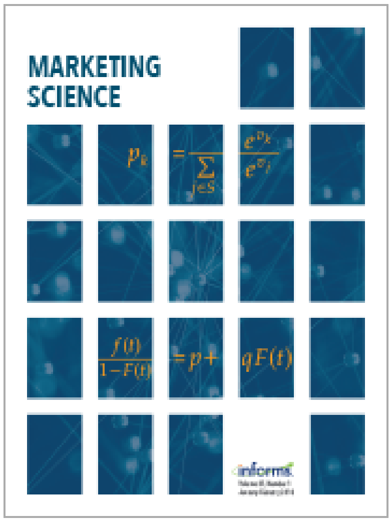

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Research Note

Using Basket Composition Data for Intelligent Supermarket Pricing

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How can supermarkets use the vast data they have to design strategies to compete for large-basket shoppers, potentially their most profitable customers? We say, analyze the data to glean basket composition of heterogeneous consumers. Of theoretical and practical interest is the question, will our suggestion improve supermarket profits, and if so, by what pricing strategies? By answering this we can also answer the question, do results of extant research on single-product marketing that using such information intensifies competition and lowers profits, generalize to multiproduct marketing by supermarkets that carry several products, and whose patrons purchase multiple items? We derive equilibrium data-based intelligent pricing strategies that also produce increased supermarket profits. What is more interesting is our result that data analysis is profitable whether or not a competitor undertakes data analysis. If not too costly, implementing data analysis is a dominant strategy. Moreover, with comprehensive data analysis connecting basket information and household data, stores can increase profits further by targeting rewards at individual households, thereby segmenting the market more completely. In contrast to past research findings, we show that for supermarkets, even under competition, use of information on past purchases enables intelligent pricing, better segmentation, and higher profits.

Key words: basket size; competition; consumer data-analytics; game theory; supermarkets; price discrimination; intelligent pricing; retailing; reward cards; reward programs
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1. Introduction

Advances in information technology and the precipitous drop in the price of storage media have made it possible for supermarkets to collect vast amounts of data on their customers. But as Simon Uwins, marketing director of Tesco P.L.C., says, "You can have all the data you want, but the key is to use them to ask the right questions" (Humby and Hunt 2003, p. 112). In this paper we propose that supermarkets would benefit by analyzing the composition of shopping baskets. In particular, we expect such analysis to lead to intelligent and profitable pricing. While we focus on the composition of shopping baskets, Bell and Lattin (1998) examined the impact of basket size on consumers' choice of store format holding the stores' pricing strategies as exogenous. Our paper adds to past research because it provides the first analysis of the impact of basket composition on supermarket pricing. A major contribution of this paper is to demonstrate that one of the "right questions" to ask of the large data that supermarkets can access is, "Who buys what?" We show that answering this question leads to better pricing.

Another issue we address in this paper is whether it is profitable to undertake target marketing, or more generally, to invest resources for collecting the needed data to learn the differences between customer segments. While past research (Shaffer and Zhang 1995, Chen 1997, Fudenberg and Tirole 2000, Chen and Iyer 2002) has examined the targeting problem in contexts where firms compete with a single product, we focus on multiproduct marketing characterized by stores that carry multiple goods and on some consumers that buy multiple goods. We investigate targeting in multiproduct marketing by studying a model of two supermarkets that compete for multiple segments of consumers: These segments differ in both the size and composition of their shopping baskets. We show that investment in costly data-analytics to learn basket composition can be profitable for both competitors because of a better ability to target the segments using intelligent pricing. This differs from the results of past work of Shaffer and Zhang (1995), Chen (1997), Fudenberg and Tirole (2000), and Chen and Iyer (2002) that show targeting to be an unprofitable strategy under competition, although it might be profitable for a monopolist.[1] The reason offered by them is that using information on (past) consumer behavior

[1] An analogous result is obtained in the case of pricing in the presence of a learning curve: While a monopolist benefits from foresight, leading to lower prices, under competition myopic pricing

intensifies price competition and lowers firms' profits. Villas-Boas (2004b) demonstrates how under certain conditions even a monopolist could be worse off with additional information on its consumers. More recently, others have found that targeting could indeed be profitable for one or both competing firms under certain circumstances. Specifically, Shaffer and Zhang (2002) have shown that targeting can be profitable for one of two firms if competing firms are asymmetric, and Chen et al. (2001) find targeting to be profitable if targetability is sufficiently imperfect. Thus, there continues to be doubt of the value of using purchase history to formulate pricing decisions for single-product marketing, except possibly in the special cases identified by Shaffer and Zhang (2002) and Chen et al. (2001). We find in our model that data-analytics and attendant targeting are profitable for competitors engaged in multiproduct marketing under quite general conditions. Our result holds even if the competing stores are symmetric and targetability is perfect (see §3.3). Therefore, it is important to understand that the value of using consumer information for targeting, and specifically devising pricing strategies, depends on the context. In the context of multiproduct marketing as exemplified by supermarkets and department stores, using information to target different consumer segments is likely to lead to higher profits.

2. Model of Data-Analytics Programs

We analyze retail competition by supposing that consumers can choose to shop at one of two competing supermarkets to buy one or more goods they are in the market for. The retailers are assumed to compete for five segments of consumers.[2] We next formally describe our model assumptions with respect to consumers, retailers and the game structure of retail competition.

2.1. Consumers

Assumption 1. *There are five types, or segments, of consumers, indexed by t. Types 1, 2, and 3 are in the market for one unit of good 1, 2, and 3, respectively. Types 4 and 5 are in the market for one unit each of two of the three goods. There is a fraction α of each of types 1, 2, and 3 consumers, $0 \le \alpha \le 1/3$, and a fraction $(1-3\alpha)/2$, of types 4 and 5 consumers.*

It is a fact that consumers differ in their supermarket shopping baskets. Some consumers have larger baskets than others. We capture this by letting types 4 and 5 have larger baskets than others. Consumers also differ in their basket—meaning, for example, that some baskets contain baby food while others contain hair coloring. We capture this by specifying different consumer types within a basket size. In practice, consumer baskets contain more than one or two items, so the goods in our model are best interpreted as sub-baskets. Considerable heterogeneity in consumer baskets is likely in practice, but our assumption captures the key elements of heterogeneity among both small-basket and large-basket consumers and, as we will see later, also helps us to capture uncertainty in the stores' decision environment (see discussion preceding Assumption 2). The implication in Assumption 1 that the three small-basket segments are equal in size, as also the two large-basket segments can be relaxed without affecting our results.[3] Within this general model, we will also examine special cases: one in which there is only basket size heterogeneity, and another with only basket composition heterogeneity.[4]

Consumers in our model are uniformly distributed along a straight line AB of unit length, and consumer location is independent of the consumer type. The market size is normalized to 1 unit. A consumer x, $0 \le x \le 1$, is located at a distance x from A and $(1-x)$ from B. Each consumer incurs a transportation cost of $c/2$ per unit distance. In addition to basket heterogeneity captured by Assumption 1, this assumption implies that consumers are also heterogeneous by virtue of their locations. All consumers are willing to pay \$$R$ per unit of any of the three goods.[5] Each store

by all firms would be preferable to competition with foresight (Rao and Bass 1985).

[2] We will use the terms *retailers*, *stores*, and *supermarkets* interchangeably throughout the paper.

[3] Details of this analysis are available from the authors upon request.

[4] Readers might wonder whether it would make a difference if there were three segments of large-basket shoppers comprising goods $(1,2)$, $(2,3)$, and $(3,1)$, or perhaps a super large-basket segment that buys all three goods. Obviously, the details of pricing strategy would depend on the exact type of heterogeneity, but the main results would not change. Given our assumption of known segment sizes, we have chosen a sufficiently rich type of heterogeneity that allows a full range of outcomes and is able to highlight the effect of basket information on prices. Alternative approaches could have a more (or less) elaborate type of basket heterogeneity but unknown segment sizes. As will become obvious later, our main findings span the full range of equilibrium outcomes, and in this sense our assumption is quite general.

[5] In practice, consumers differ in their willingness to pay for any good so our assumption must be seen as a way to keep the analysis simple. Furthermore, while consumers have a common reservation price of \$$R$/unit they will consider purchasing their basket at a store only if the price is lower than R or $2R$ as the case may be. To see this, consider a consumer of type 1 located x units away from store i. A necessary (but not sufficient) condition for this consumer to purchase good 1 at store i is $p_1^i \le R - cx$. As we will see later, our results do not depend on the exact value of R relative to other parameters. It is easy to relax the assumption that all goods have the same reservation price, but that would turn our attention to the relative profitability of goods, which is not the focus of our investigation.

advertises the price of the three goods so that consumers know the prices of all goods before deciding on a store at which to shop.

2.2. Retailers

There are two competing retailers (supermarkets) located at either end of AB, with store A at the left end and store B at the right end. We index stores by i, $i = \{A, B\}$. Each retailer carries three goods that are neither complements nor substitutes, indexed by j, $j = 1$, 2, and 3, and both retailers face identical per unit costs, which without loss of generality we set to zero for all j.

Retailers in our model carry multiple goods reflecting our interest in supermarket pricing strategies, and the assumption that both carry the same goods that are neither complements nor substitutes is reasonable because it reflects the reality of supermarkets carrying identical brands of shampoo and cake mix, for example. The three-goods restriction simplifies the exposition without affecting results, and it is best to view the three goods as three baskets. In our model, retailers know the size of all segments, meaning they know α. However, retailers do not know the composition of items in large baskets. Given our assumption of equal segment sizes within a basket size, knowing α is sufficient to learn the sizes of all segments. The composition of baskets has relevance for only large-basket segments. While consumers know the composition of their basket, retailers in our model do not know it. It is common knowledge among consumers and retailers that types 4 and 5 are in the market for two goods. The identity of the goods in their basket is private information held by types 4 and 5 consumers.[6] Retailers in our model can choose to learn the basket composition as elaborated in the next assumption.

Assumption 2. *Each retailer can choose to learn basket composition by collecting and analyzing data at a fixed cost of F and a per-customer cost of v. Without loss of generality we set v to zero.*

In practice, stores can obtain basket information in a variety of ways. For one, they could analyze aggregate sales of each good to infer basket composition, a feasible option in our model. However, if stores don't know segment sizes, they would need data on more than just aggregate sales. We can then imagine stores analyzing cash register receipts to learn both segment size and basket composition. In practice, unlike in our model, consumer purchases vary over shopping trips, necessitating analysis of data across shopping trips to learn the true nature of basket composition. This can be done by tracking purchases of individual households. Thus, although analyzing cash register receipts is sufficient for learning the parameters of our model, a more realistic interpretation would suggest the need for a sophisticated tracking mechanism.[7] Regardless of how data are obtained, the analysis would be key to learning basket of consumers. We label this consumer data-analytics.[8] This would entail a cost, even if it involved only tabulation, and likely a high cost because supermarkets carry thousands of SKUs. Historically, supermarkets have used data from such sources as IRI and ACNielsen, and sometimes have collected their own data. The key point to note here is that data-analytics is costly.

Let $l^i = 1$ (or 0), be an indicator variable denoting firm i's decision of whether or not to invest in a data-analytics program that collects/analyzes household data, revealing the household's basket composition. Specifically, a data-analytics program enables the retailer to learn which two goods types 4 and 5 consumers buy. Following Assumption 1, types 4 and 5 consumers have two goods in their basket, and the baskets differ. Note that one of the three goods would be present in both baskets. We will label this as the *common good*. We label any item other than the common good as a *unique good*. Denote s, $s = 1, 2, 3$, respectively, to be the state corresponding to good, s being the common good. Denote μ_s^i to be retailer i's probability assessment that $s = 1$, 2, and 3, respectively, and $\boldsymbol{\mu}^i$ to be the corresponding (row) vector, with $\mu_1^i + \mu_2^i + \mu_3^i = 1$. It is necessary to specify $\boldsymbol{\mu}^i$ corresponding to $l^i = 0$. We do this in the next assumption.

Assumption 3. *A retailer who does not institute a data-analytics program has a diffuse prior $\boldsymbol{\mu}_0^i$ on s. In other words, $\boldsymbol{\mu}_0^i = (\boldsymbol{\mu}^i \mid l^i = 0) = [1/3\ \ 1/3\ \ 1/3]$. Furthermore, it is known to both retailers that a retailer with a data-analytics program knows s. This is common knowledge.*

Because there is no other source of information on consumers in our model, it makes sense to assume that stores have a diffuse prior on s in the absence of a data-analytics program.[9] The assumption of common knowledge follows simply from the recognition by each retailer that the other has no potential source of

[6] Thus the source of uncertainty in the stores' decision environment arises from incomplete information on the composition of large baskets. In practice stores may know the composition of the large baskets but not the sizes of the different segments or may be uninformed both about the composition and the sizes of the different segments. Our results are not sensitive to the source of uncertainty.

[7] Reward or loyalty cards can be one such mechanism.

[8] We thank the area editor for making this suggestion.

[9] The assumption that priors are diffused is not critical to our findings. For data-analytics to be valuable there must be some initial source of uncertainty so priors cannot be degenerate. Our results will hold as long as there is a step improvement in knowledge of the state with the data-analytic programs. We thank the Area Editor for this observation.

Table 1 **Probability Assessments Conditional on Stores' Decision on Data-Analytics**

Stores' decisions (I^A, I^B)	μ^A	μ^B
(0, 0)	[1/3 1/3 1/3]	[1/3 1/3 1/3]
(0, 1)	[1/3 1/3 1/3]	$\boldsymbol{\theta}_s$
(1, 0)	$\boldsymbol{\theta}_s$	[1/3 1/3 1/3]
(1, 1)	$\boldsymbol{\theta}_s$	$\boldsymbol{\theta}_s$

information on consumers other than a data-analytics program.

Denote $\boldsymbol{\theta}_s$ to be the probability vector corresponding to the true state of s. If a retailer institutes the data-analytics program, then he can discover the true state of s.[10] Thus,

$$(\boldsymbol{\mu}^i \mid l^i = 1) = \boldsymbol{\theta}_s, \tag{1}$$

where $\boldsymbol{\theta}_1 = [1\ 0\ 0]$, $\boldsymbol{\theta}_2 = [0\ 1\ 0]$, and $\boldsymbol{\theta}_3 = [0\ 0\ 1]$.

We model store competition as a single-period game with two stages. In the first stage, stores simultaneously decide whether or not to implement a data-analytics program. In the second stage, they choose prices of the three goods simultaneously based on the probability assessments in Table 1, that depend on whether or not a store implemented a data-analytics program in the first stage. We might wonder if a store can learn the basket composition by observing its rival's pricing. Such a possibility has no force in our model because prices are simultaneously determined. Now the question arises of how our model would apply in practice where firms compete for more than one period. However, in this case there would also be other forces at work. Supermarkets carry thousands of goods with multiple brands, so heterogeneity of basket composition would also be considerable, and shopping baskets would contain many goods with several common goods. Thus, it would be reasonable to assume that a store that does not have a data-analytics program would remain substantially ignorant of basket composition if it relied only on its rival's prices. In this way our assumption can be seen as a reasonable model of reality.

3. Analysis of Data-Analytic Programs

Let p_j^{is} and p_j^{i0} denote the price of item $j \in \{1, 2, 3\}$ in state s, chosen by retailer $i \in \{A, B\}$, when $l^i = 1$ and $l^i = 0$, respectively. Note that the price would depend on l^i because by implementing a data-analytics program (in first stage) a store can get information on the common good for use in pricing decisions (in second stage). Let P^{is} and P^{i0} denote the column vector of the prices chosen by store i when $l^i = 1$ and $l^i = 0$, respectively.

[10] The timing of the availability of information is spelled out next.

3.1. Characterization of Retail Demand and Profits

Each consumer makes his store choice based on his basket, the stores' prices, and his location x. These consumer choices determine the share of each type of consumer that the two stores attract. Let $g_t^i(P^i, P^k)$, $t = 1, 2, 3$ denote the share of small-basket consumers choosing store i. To compute this, first note that a consumer located at x purchases good j from store A iff

$$R - cx - p_j^A \geq \max\{R - c(1-x) - p_j^B, 0\}.$$

The LHS of the above inequality denotes the net utility from buying good j at store A, and the RHS that from buying at store B, or choosing to not buy at all, whichever is higher. Similarly, we can obtain the choice rule for a consumer to choose store B, and the store choice rules imply that a consumer in segment $t = \{1, 2, 3\}$, located at $(p_j^B - p_j^A + c)/2c$ is indifferent to buying at either store $\forall\, j,\ t \in \{1, 2, 3\}$.[11] The demand, $g_t^A(P^A, P^B) = \alpha(p_j^B - p_j^A + c)/2c$, as in the standard Hotelling model.

Turning to type 4 and 5 consumers, recall that the common good in their baskets is one of goods 1, 2, or 3, with the corresponding states being $s = 1$, 2, or 3; for example, when $s = 1$, type 4 consumers buy $\{1, 2\}$ and type 5 consumers buy $\{1, 3\}$, or vice versa. Denote the share of the large-basket consumers in state s at store i by $h_{ts}^i(P^i, P^k)$, $t = 4, 5$. Suppose $s = 1$. Then, a consumer in segment 4 located at x will purchase the basket comprising goods 1 and 2 from store A iff

$$\begin{aligned} &2R - cx - p_1^A - p_2^A \\ &\quad \geq \max\{2R - c(1-x) - p_1^B - p_2^B,\ 2R - c - p_1^A - p_2^B, \\ &\qquad\qquad 2R - c - p_1^B - p_2^A,\ 0\}. \end{aligned}$$

The LHS of the above inequality denotes the net utility of a type 4 consumer located at x from buying the basket at store A, and the RHS that from buying the basket at store B, or buying one good at store A and the other at store B, or choosing to not buy at all, whichever is highest. Similarly, if the net utility from buying at store B is higher, then the consumer would buy form store B. Given this choice rule, a type 4 consumer located at $(p_1^B + p_2^B - p_1^A - p_2^A + c)/2c$ is indifferent to buying the basket at either store.[12] Hence, the demand from consumers in segment 4 in state 1, at store A is

$$h_{41}^A(P^A, P^B) = \frac{(1-3\alpha)\left(p_1^B + p_2^B - p_1^A - p_2^A + c\right)}{4c},$$

[11] We are implicitly assuming that shopping at either store will yield positive net utility to the marginal consumers. This turns out to be the case in equilibrium.

[12] This would be true if c is sufficiently large.

as in Lal and Matutes (1994). Similar analysis of type 5 consumers' store choice problem yields the demand from consumers in segment 5 in state 1, at store A:

$$h_{51}^{A}(P^{A},P^{B})=\frac{(1-3\alpha)\left(p_1^B+p_3^B-p_1^A-p_3^A+c\right)}{4c}.$$

Using the same procedure, we can compute demand from these two segments in the other states, $h_{ts}^{i}(P^{i},P^{k})$, $t=\{4,5\}$, $s=\{2,3\}$.

Demand and Pricing Strategies. By implementing a data-analytics program in the first stage, retailer i can learn the identity of the common good (or the true state, s) at the beginning of the second stage. In that case $g_t^i(P^i,P^k)$ represents the demand of retailer i in segment t, $t=\{1,2,3\}$ and $h_{ts}^{i}(P^{i},P^{k})$ represents its demand in segment t, $t=\{4,5\}$ when the true state is s. However, when store i decides not to implement a data-analytics program in the first stage it remains ignorant about the common good in the basket of type 4 and 5 consumers. In this case, we must derive the *expected* demand. First, consider the demand in each of the segments 1 through 3. Denote $G_t^i(\cdot)$ to be the expected demand at store i in segment t, $t=1,2,3$. Then, for any choice $\mathbf{P}^i$ by store i we have

$$G_t^i(P^i;l^k)=\begin{cases}\displaystyle\sum_{s=1}^{3}\mu_s^i g_t^i(P^i,P^{k0}), & \text{if } l^k=0\\ \displaystyle\sum_{s=1}^{3}\mu_s^i g_t^i(P^i,P^{ks}), & \text{if } l^k=1\end{cases}$$
$$t=\{1,2,3\},\ i,k\in\{A,B\}. \quad (2)$$

For the expected demand in segments 4 and 5, let $H_{ts}^i(P^i;l^k)$ denote the demand in segment t, $t=\{4,5\}$ that retailer i obtains given the competitor's first stage decision l^k and state s. Then, we have

$$H_{ts}^i(P^i;l^k)=\begin{cases}h_{ts}^i(P^i,P^{k0}), & \text{if } l^k=0\\ h_{ts}^i(P^i,P^{ks}), & \text{if } l^k=1\end{cases}$$
$$t=\{4,5\},\ s=\{1,2,3\},\ i,k\in\{A,B\}. \quad (3)$$

Consider two cases, in turn.

First, when $l^i=0$ the expected profits of retailer i, π_0^i, are given by

$$\begin{aligned}\pi_0^i(P^{i0};l^k)&=\sum_{t=1}^{3}G_t^i(P^{i0};l^k)p_t^{i0}\\&+\left\{\begin{array}{l}\mu_1^i\left(H_{41}^i(P^{i0};l^k)(p_1^{i0}+p_2^{i0})+H_{51}^i(P^{i0};l^k)(p_1^{i0}+p_3^{i0})\right)\\+\mu_2^i\left(H_{42}^i(P^{i0};l^k)(p_1^{i0}+p_2^{i0})+H_{52}^i(P^{i0};l^k)(p_2^{i0}+p_3^{i0})\right)\\+\mu_3^i\left(H_{43}^i(P^{i0};l^k)(p_1^{i0}+p_3^{i0})+H_{53}^i(P^{i0};l^k)(p_2^{i0}+p_3^{i0})\right)\end{array}\right\}\end{aligned} \quad (4)$$

In (4) the first term corresponds to the expected profits from small-basket shoppers in segments 1, 2, and 3. The profit in each segment is the price of the good that segment buys times the expected demand in that segment. The latter, as specified in (2), depends on retailer i's price, the price of that good chosen by the competitor k given l^k and i's assessment $\boldsymbol{\mu}^i$. The second term is the expected profit from segments 4 and 5 given by the sum of the prices of the two goods that consumers in each segment buys times retailer i's expected demand in each state, s, weighted by firm i's beliefs. The demand, as specified in (3), depends on retailer i's prices, the prices chosen by the competitor k given l^k, and i's assessment $\boldsymbol{\mu}^i$.

Second, when $l^i=1$, retailer i's profits, π_s^i, are given by

$$\begin{aligned}\pi_s^i(P^{is};l^k)&=\sum_{t=1}^{3}g_t^i(P^{is},P^k)p_t^{is}\\&+\begin{cases}H_{41}^i(P^{i1};l^k)(p_1^{i1}+p_2^{i1})\\ \quad +H_{51}^i(P^{i1};l^k)(p_1^{i1}+p_3^{i1}), & \text{if } s=1\\ H_{42}^i(P^{i2};l^k)(p_1^{i2}+p_2^{i2})\\ \quad +H_{52}^i(P^{i2};l^k)(p_2^{i2}+p_3^{i2}), & \text{if } s=2\\ H_{43}^i(P^{i3};l^k)(p_1^{i3}+p_3^{i3})\\ \quad +H_{53}^i(P^{i3};l^k)(p_2^{i3}+p_3^{i3}), & \text{if } s=3.\end{cases}\end{aligned} \quad (5)$$

As in (4), the first term in (5) corresponds to profits from segments 1–3 and the second term to profits from segments 4 and 5 when retailer i knows the state to be s. Note that in contrast to (4) we do not take expectations with respect to state in (5) because the state is known. Furthermore, the prices in (5) are state contingent. Corresponding to each outcome of the first stage, the retailers must determine their prices that maximize their profits in (4) or (5) given their probability assessments. For firm i, if $l^i=0$, the equilibrium choice of prices, P^{i0*} is given by

$$P^{i0*}=\arg\max[\pi_0^i(P^i;l^k)],\quad i,k=\{A,B\}. \quad (6)$$

For firm i, if $l^i=1$, the equilibrium choice of i, P^{is*} is given by

$$P^{is*}=\arg\max[\pi_s^i(P^i;l^k)],\quad i,k=\{A,B\},\ s=\{1,2,3\}. \quad (7)$$

The Nash equilibrium prices in (6) and (7) maximize the expected profits of each store.

Given these pricing strategies, retailers must determine whether or not to implement a data-analytics program in the first stage. Denote $\Pi^{i*}(l^i,l^k)$ to be the equilibrium profits of retailer i given that the outcome in stage 1 is (l^i, l^k), where

$$\Pi^{i*}(l^i, l^k) = \begin{cases} \pi_0^i(P^{i0*}; l^k), & l^i = 0,\ l^k = 0 \\ \pi_0^i(P^{i0*}; l^k), & l^i = 0,\ l^k = 1 \\ \sum_{s=1}^{3} \mu_0^i \pi_s^i(P^{is*}; l^k), & l^i = 1,\ l^k = 0 \\ \sum_{s=1}^{3} \mu_0^i \pi_s^i(P^{is*}; l^k), & l^i = 1,\ l^k = 1 \end{cases}. \quad (8)$$

The first two entries in (8) differ from the third and fourth entries because at the time of the decision to invest in data-analytics programs, firm i does not know which state will be realized. Consequently, we need to weigh the profit in a given state by the probability that state is realized to compute the ex-ante profit. The first stage decision is then a Nash equilibrium to the 2×2 data-analytics *game* displayed in Table 2. In Table 2 the entries represent expected profits of the retailers corresponding to their choice of l. We next turn to exploring the properties of this equilibrium. In particular, we investigate the profitability of data-analytics programs.

3.2. Profitability of Data-Analytics Programs

In this section we present our key result that data-analytics programs can help stores make better pricing decisions and thereby increase profits *even when both implement the programs*. This highlights the informational role of data-analytics programs and the fact that pricing based on such information does not dissipate profits through competition. We first characterize the equilibrium prices conditional on first-stage outcomes that induce four subgames in the second stage corresponding to $l^A = l^B = 0$, denoted $(0, 0)$; $l^A = l^B = 1$, denoted $(1, 1)$; $l^A = 0$, $l^B = 1$, denoted $(0, 1)$; and $l^A = 1$, $l^B = 0$, denoted $(1, 0)$. These four subgames correspond respectively to the cases in which data-analytics programs are implemented by neither store, both stores, by store B but not store A, and finally by store A but not store B. Because firms in our model are symmetric it is sufficient to analyze only the first three subgames. Equilibrium prices and profits for these three subgames are characterized in Lemmas 1–3. We then work backward to characterize

Table 2 **Data-Analytics Game Pay-Offs**

	Retailer B, l^B: 0	Retailer B, l^B: 1
Retailer A, l^A		
0	$\Pi^{A*}(0, 0)$, $\Pi^{B*}(0, 0)$	$\Pi^{A*}(0, 1)$, $\Pi^{B*}(1, 0)$
1	$\Pi^{A*}(1, 0)$, $\Pi^{B*}(0, 1)$	$\Pi^{A*}(1, 1)$, $\Pi^{B*}(1, 1)$

equilibrium strategies of stores in both the pricing and data-analytics game in the first stage. This is done in Proposition 1.

3.2.1. Neither Retailer Has a Data-Analytics Program. First consider the case in which neither store implements a data-analytics program in the first stage.

Lemma 1. *When neither store implements a data-analytics program* ($l^A = l^B = 0$), *then*

$$p_j^{i0*} = \frac{c(2-3\alpha)}{(4-9\alpha)}, \quad \forall j = \{1, 2, 3\}, \forall i = \{A, B\}$$

and,

$$\pi_0^i(P^{i0*}; l^k) = \frac{c(2-3\alpha)^2}{2(4-9\alpha)}, \quad i, k = \{A, B\},\ i \neq k.$$

Proof. See the appendix.[13]

In this subgame stores do not know the state s (identity of the common good), and so set prices of all three items to be the same.[14] To get an insight into the equilibrium pricing strategies, first consider the case when there are no large-basket shoppers ($\alpha = 1/3$). The equilibrium price of each good turns out to be c. Because there is no overlap in consumer baskets if $\alpha = 1/3$, we find that each good is priced at c. In other words, there is *complete segmentation* of the market. Next, if the size of both large- and small-basket shopper segments are greater than zero ($0 < \alpha < 1/3$), the equilibrium price of each good, and therefore of each small basket, is less than c. In other words, the large-basket shoppers exert a positive externality on small-basket shoppers. The intuition here is that stores would like to compete aggressively for large-basket shoppers by offering lower prices on the items in their basket. This gives small-basket shoppers higher consumer surplus than they would get absent large-basket shoppers, so the market is not completely segmented. However, note that in this case the price of the large basket is $2p_j^{i0*} = 2c(2-3\alpha)/(4-9\alpha) > c$. Finally, if there are no small-basket shoppers ($\alpha = 0$), we find that the equilibrium price of each good is $c/2$. Although in this case the price of the individual good is less than the price when $\alpha = 1/3$, the basket price is c. Basket heterogeneity causes equilibrium basket prices to be different from c, which we will elaborate on in the next section.

3.2.2. Both Retailers Have Data-Analytics Programs. Now consider the case when both stores implement a data-analytics programs.

[13] Proofs of all lemmas and propositions are in the appendix.

[14] Symmetry in prices across the three goods results because of symmetry in the size of the small- and large-basket segments, symmetry in priors and symmetry in reservation price of the three goods. Our findings are not sensitive to these assumptions.

Lemma 2. *When both stores implement a data-analytics program ($l^A = l^B = 1$), then*

$$p_j^{is*} = \frac{c(1-\alpha)}{(3-7\alpha)}, \quad j = s, \forall i = \{A, B\},$$

$$p_j^{is*} = \frac{2c(1-2\alpha)}{(3-7\alpha)}, \quad j \neq s, \forall i = \{A, B\},$$

and,

$$\pi_s^i(P^{is*}; l^k) = \frac{3c(1-\alpha)(1-2\alpha)}{2(3-7\alpha)}, \quad i \neq k, \ i, k = \{A, B\}, \ s = \{1, 2, 3\}.$$

We can obtain several interesting insights by comparing the prices and profits in this subgame $(1, 1)$ with that in the subgame $(0, 0)$. First, in any state s, for the common good j, $j = s$, we have

$$p_j^{is*} - p_j^{i0*} = -\frac{c(2-10\alpha+12\alpha^2)}{(3-7\alpha)(4-9\alpha)} \leq 0, \quad \forall \alpha \leq 1/3, \forall i = \{A, B\}.$$

For unique goods, $j \neq s$, we find

$$p_j^{is*} - p_j^{i0*} = \frac{c(2-11\alpha+15\alpha^2)}{(3-7\alpha)(4-9\alpha)} \geq 0, \quad \forall \alpha \leq 1/3, \forall i = \{A, B\}.$$

These two inequalities together imply that the large basket is priced lower when both stores have data-analytics programs.[15] In contrast, two of the three smaller baskets are higher priced. Note that in this case, lowering the price of the large basket would necessarily lower the price of at least one small basket because of the assumed type of basket heterogeneity. The key intuition here is that the stores would like to lower the price of the large baskets because the large-basket customers represent greater profit potential, so competition for them is keen. The dilemma facing stores, then, is how to offer higher value to large-basket shoppers but not to the small-basket shoppers. The exact manner in which this could be achieved would depend on the nature of basket heterogeneity.

Basket Heterogeneity and Providing Value to Large-Basket Shoppers. We can understand the role of basket heterogeneity better by examining special cases of our model. Recall from the discussion following Lemma 1, complete segmentation is achieved when the market consists of only small-basket shoppers or only large-basket shoppers. In the former case the price of all items is c, as in Lal and Matutes (1994). Similarly, if there are only large-basket shoppers, the equilibrium price of each item is $c/2$, so that both baskets are priced at c and information on basket composition is not useful. Thus, we see that within our model information on *basket composition is useful only if there is basket size heterogeneity*. Next, we can ask if basket size heterogeneity is sufficient to make the information useful, or if it is also necessary to have basket composition heterogeneity (within a) given basket size.

Consider the case with no basket composition heterogeneity within a basket size. In other words, there is a segment of small-basket shoppers who all desire the same product and a segment of large-basket shoppers who all desire the same basket. In this case, the good purchased by small-basket shoppers can be either common (to both types of shoppers) or unique, and a data-analytics program would reveal that. If it is the unique good, its equilibrium price would be c, while that of the other two goods would be $c/2$. If it is the common good, its equilibrium price would be c, and the other two goods would be priced at 0. Thus, learning basket composition is useful for pricing in this case. An interesting point to note here is that the common good is bought by both types of consumers and therefore has the highest sales. Yet, it is priced higher than a good whose sales are lower. We see, therefore, that knowing which good sells more does not necessarily help in the optimal pricing of goods. Rather, what is useful is the information on who buys what goods. Consequently, the role of data-analytic programs goes beyond simply identifying high-volume items. Said differently, it is not enough to know just what the large-basket shoppers are buying, but it is equally important to know the items they purchase that are distinct from those purchased by small-basket shoppers. In this way, we can see that by conducting data-analytics both stores are able to compete effectively, and intensely, for the large-basket shoppers and reduce the subsidy to certain small-basket shoppers.

Another point worth noting here is that in this case, with just two segments that differ in basket size but not in composition within the segments, there is no subsidy to small-basket shoppers because of the presence of large-basket shoppers. Indeed, basket information leads to complete segmentation of the consumer types. In fact, if there is composition heterogeneity within the large but not the small-basket segment, basket composition information once again leads to complete segmentation of the market. On the other hand, if composition heterogeneity exists within the small but not the large-basket segment, basket composition information is not sufficient to completely segment the market. In reality, both large- and small-basket shoppers would exhibit

[15] $$p_s^{is*} + p_j^{is*} - (p_s^{i0*} + p_j^{i0*}) = -\frac{c\alpha(1-3\alpha)}{(3-7\alpha)(4-9\alpha)} \leq 0, \quad j \neq s, \forall \alpha \leq 1/3, \forall i = \{A, B\}.$$

composition heterogeneity, making it difficult to completely segment the market based only on composition information.

Impact on Profits. The next interesting question is the impact of data-analytics programs on profits. Comparing the equilibrium profits in the two subgames, we find

$$\pi_s^i(P^{is^*}; l^k = 1) - \pi_0^i(P^{i0^*}; l^k = 0) = \frac{c\alpha(1-3\alpha)^2}{2(3-7\alpha)(4-9\alpha)} \geq 0, \quad \forall\, \alpha \leq 1/3,\ i = \{A, B\}.$$

We can see that profits are higher if both stores implement a data-analytics program than if neither implemented it. This happens even when more consumers (fraction $1 - 2\alpha \geq 1/2$ if $\alpha \leq 1/4$) benefit from lower prices, and fewer consumers (fraction $2\alpha \leq 1/2$) face higher prices in the subgame $(1, 1)$. It is natural to ask if this is due to the assumed symmetry in the size of the three small-basket segments. It turns out that lack of symmetry in segment sizes does not overturn this result.[16]

3.2.3. Only One Retailer Has a Data-Analytics Program. If only one store implemented a data-analytics program, would that lead to higher profits to either or both stores? A related question is, should a store implement a data-analytics program if its competitor does so? Suppose retailer A does not implement a data-analytics program but retailer B does. In this case, B will know the identity of the common good while A will not, and A will therefore believe that items 1–3 are equally likely to be the common good. Consequently, it will set equal prices for all three items. Store B, on the other hand, will set prices depending on the state.

Lemma 3. *When one store implements a data-analytics program and the other does not ($l^B = 1$ and $l^A = 0$), then*

$$p_j^{A0^*} = \frac{c(2-3\alpha)}{(4-9\alpha)}, \quad \forall\, j = \{1, 2, 3\}$$

$$p_j^{Bs^*} = \frac{5c - 3c\alpha(6-5\alpha)}{(3-7\alpha)(4-9\alpha)}, \quad j = s,$$

$$p_j^{Bs^*} = \frac{14c - 57c\alpha(1-\alpha)}{2(3-7\alpha)(4-9\alpha)}, \quad j \neq s$$

$$\pi_0^A(P^{A0^*}; l^B) = \frac{c(2-3\alpha)^2}{2(4-9\alpha)},$$

and

$$\pi_s^B(P^{Bs^*}; l^A) = \frac{3c\big(16 - \alpha(85 - \alpha(146 - 81\alpha))\big)}{8(3-7\alpha)(4-9\alpha)}.$$

As in subgame $(0, 0)$, retailer A, who does not have a data-analytics program, charges the same price for all items. In contrast, retailer B, who implements a data-analytics program, charges a lower price than A for the common good but a higher price for the unique goods.

Next, what is the effect on profits to retailer B who implements a data-analytics program? As might be expected, its profits are higher in this case than in subgame $(0, 0)$ but, interestingly, its profits are *lower* than what the retailer would obtain in subgame $(1, 1)$. This is because its competitor's prices of the unique goods are too low. As we saw in Lemma 2, the higher profits in the subgame $(1, 1)$ resulted from the higher prices on unique goods. Because prices are strategic complements in this model, store B—which knows the identity of the common good—can raise its price on the unique goods further if its competitor A also had the same information.

3.2.4. The Data-Analytics Decision. We now solve for the subgame perfect equilibrium of this two-stage game using the results in Lemmas 1–3.

Proposition 1. *Assume* $F \leq F^* = c(1-3\alpha)^2\alpha / 8(3-7\alpha)(4-9\alpha)$. *Then implementing a data-analytics program is a dominant strategy, so in equilibrium both stores implement data-analytics programs.*

Proposition 1 says that regardless of what its competitor does, it is best for a store to implement a data-analytics program if the cost F is not too large. Note that if there are no large-basket shoppers ($\alpha = 1/3$), $F^* = 0$; and similarly, if there are no small-basket shoppers ($\alpha = 0$), once again $F^* = 0$. Thus, data-analytics programs can increase profits only if there is basket size heterogeneity. The key intuition from our analysis is that by implementing a data-analytics program, retailers acquire information that enables them to price intelligently in the presence of basket heterogeneity. In particular, the data-analytics program allows retailers in our model to compete for large-basket shoppers without subsidizing the small-basket shoppers too much. One possible way to accomplish this, depending on the nature of the composition heterogeneity, would be to identify a good that large-basket shoppers buy but not small-basket shoppers, and lower the price of that good. Humby and Hunt

[16] In our model we have two assumptions that could be thought to drive our results. In particular, we have assumed that small-basket shopper segments are of equal size, a certain kind of symmetry. In reality, this need not be the case and the segments that buy the unique goods could be large or small relative to the segments that buy the common good. Another assumption that we have made is that firms know the size of the segments but not the composition of the baskets. In practice, stores could be informed about basket composition but not segment sizes. Our findings are robust to a relaxation of these assumptions. Details of these extensions are available in a technical supplement at http://mktsci.pubs.informs.org.

(2003, pp. 146–147) assert that the idea of using basket composition information to address different segments using this "intelligent" pricing strategy has been one of the key drivers of the success of Tesco, a leading supermarket chain in the United Kingdom. They note that "If…data could identify the products that were bought by price-conscious shoppers, but not by the rest of us, then lowering those prices would have a huge benefit for them, at the lowest possible cost for Tesco." While Tesco was interested in addressing "the price conscious segment," we show how this sort of strategy could be profitable under any segmentation scheme, as is the case in our model in which segmentation is based on basket size, which in turn translates into "more, and less, profitable customers." What is more important is that we provide a rigorous theoretical analysis of this strategy and its impact on profits under competition. We also establish that while the best product to lower the price on would, under some conditions, be a unique good bought by the targeted segment as practiced by Tesco, other conditions would require a different pricing strategy of lowering price on another good (whose exact identity would depend on how many segments exist and the basket composition heterogeneity over these segments). In this way we provide theoretical insights into pricing that would be of practical value. We also obtain the interesting result that even if a rival offers a data-analytics program, a retailer's profits from data-analytics do not decrease as a result of increased competition. Indeed, profits increase if the rival also implements a data-analytics program. This result is in contrast to extant work (Shaffer and Zhang 1995, Fudenberg and Tirole 2000) that finds the use of information to target results in more intense competition, in turn decreasing profits. We find that such targeting does increase intensity of competition for some consumers but also results in reduced competition for others, the net effect being one of higher profits.

3.3. Using Data-Analytics to Reward Large-Basket Shoppers

In targeting large-basket shoppers by identifying basket composition across basket sizes, it would seem natural to ask if targeting rewards by using household-level information on consumers, in addition to their basket composition, can increase profits further. To answer this question we use a parsimonious version of our base model. Specifically, we examine a case with three small-basket segments and one large-basket segment (say, type 4), and retain all other assumptions. This parsimonious version has the desirable feature of stores' inability to completely segment the market, even with consumer data-analytics.

If, as we have assumed, stores are restricted to charge uniform prices, then they cannot in general achieve complete segmentation. However, if data-analytics programs yield information about individual consumers, it is possible in our model to charge higher prices to *all* small-basket consumers and achieve complete segmentation. Indeed, we propose a simple mechanism that consists of stores offering rewards to large-basket shoppers; and we show how this, even under competition and even when targetability is perfect, leads to higher profits than the uniform pricing strategies.

We analyze this situation exactly as in §3, with the key difference that in addition to setting the price of the three items stores investing in data-analytics must now decide on the reward for large-basket shoppers. Formally, let $r_1^{is} \geq 0$ denote the monetary value of such a reward offered in state s by the store i if it implements a data-analytics program, and $r_0^{i0} = 0$ otherwise.[17] Our analysis leads to the following proposition.

Proposition 2. *Assume $F < F^{**} = 3c\alpha(1-3\alpha)/8(4-9\alpha)$. Then implementing a data-analytics program and offering rewards to large-basket shoppers is a dominant strategy for both stores. The equilibrium strategies are as follows:*

$$p_j^{is*} = c, \quad \forall j,\ s = \{1, 2, 3\},\ i = \{A, B\},$$
$$r_1^{is*} = c, \quad \forall s = \{1, 2, 3\},\ i = \{A, B\},$$

and,

$$\pi_s^i(P^{is*}, r_1^{is*}; I^k = 1) = \frac{c}{2}, \quad \forall i \neq k,\ i, k = \{A, B\},\ \forall s = \{1, 2, 3\}.$$

As in §3.2 we find as in the earlier cases: implementing a data-analytics program if its cost is not too large is a dominant strategy for both stores. What is more interesting is that rewards targeted at large-basket shoppers allow stores to completely segment the market and thereby increase their profits further. In contrast to equilibrium strategies in the base case with uniform pricing (Lemma 2), all small-basket shoppers now pay c. Under uniform pricing, even with data-analytics programs, competition for large-basket shoppers forces stores to lower the price of large-basket items, so small-basket shoppers purchasing that item pay less than c. With consumer household-level information, stores target rewards in addition to choosing prices strategically to compete for large-basket shoppers. The equilibrium basket price to charge each customer, regardless of basket size or composition, under competition is c. What rewards do is relax the constraints imposed

[17] Stores without data-analytics program do not know the identity of the large-basket shoppers.

Figure 1 Rewards Based on Basket Size

Note. Reprinted with permission of Albertson's, Inc.

by uniform pricing. They act like two-part tariffs: All consumers are charged a higher price, and then a discount is offered to the large-basket shoppers. Of-course, a more costly way to implement this reward mechanism would be to not target it but to allow self-selection to work by making the reward conditional on the size of basket actually bought.[18] Indeed, we have seen in recent months some supermarkets adopting precisely this strategy, as displayed in Figure 1. The Albertsons chain of supermarkets in Dallas has been sending store coupons to their "preferred customers" that offer higher discounts to consumers buying larger baskets. Finally, we should note that in frequency-based rewards (Kim et al. 2001), which are thought to increase price under competition, it is not obvious if the "loyal" customers benefit from net lower prices as a result of the reward compared to the case of no rewards. In contrast, the reward program we construct actually *lowers* the price to the large-basket shoppers. This is accompanied by higher prices to the small-basket shoppers. Thus, rewards in our model truly reward the shoppers for whom competition is greatest.

From a theoretical point of view, data-analytics programs offer particularly efficient ways to deal with pricing to consumers that are heterogeneous in their shopping baskets. Proper targeting of reward programs would obviously be profitable. However, in practice, stores face not just a few but many segments. Thus, even after targeting with reward programs that are designed in steps, it could be necessary to choose uniform prices strategically using information from consumer data-analytics. The targeting itself might be complicated by the fact that the reward would have to be tied to future purchases, and it might not be obvious what items a consumer would buy on his/her next shopping trip. At the brand level, Kopalle and Neslin (2003) show that frequency reward programs that tie rewards to future purchases can be profitable. Finally, trade promotions cause substantial fluctuations in relative costs of items, making it worthwhile to tie rewards to these items.

From a practical point of view, supermarkets that have a *reward card program* are in a good position to implement a data-analytics program. Indeed, that is best illustrated by the experience of Tesco. The motivation for reward cards has been to be able to target individual shoppers with rewards, or more generally special offers that exploit data-analytics by taking into account the preferences and buying patterns of individual households (Schlumberger Limited 1998). Thus reward cards can help in implementing segmentation strategies based not on who has the card but on purchase patterns. Continued use of promotions that restrict them to users of the reward cards, in our opinion, merely help to obtain better data so that stores would be in a position to evaluate and improve their pricing through data-analytics.[19]

Finally, we should distinguish data-analytics and reward programs from "loyalty" programs. For supermarkets, frequency rewards that are designed to provide incentives for past purchases have the effect of preventing store switching in anticipation of a future reward. This could be profitable even absent a priori consumer heterogeneity. We contemplate rewards that are designed to price discriminate across large- and small-basket consumers. This could be implemented by using only basket information to price the products profitably, or by offering rewards, or both.

[18] It is more costly in our model because of the extra mailings to the small-basket consumers. In practice, there could also be a cost because small-basket consumers might consolidate their purchases across shopping trips, and that has no effect on the ability to compete for the desirable large-basket shoppers.

[19] Although tying discounts to use of reward cards is in the nature of price discrimination, it is also the case that the overwhelming fraction of shoppers avail themselves of the lower price (for example, Minnesota Public Radio 2002). In fact, a consumer can often get the lower price simply by telling the check-out clerk that he forgot to bring the card. It would seem, therefore, that in practice price discrimination is not a key reason for linking lower prices to the use of loyalty cards by supermarkets.

4. Conclusions and Directions for Future Work

In this paper we have shown how supermarkets can price their goods intelligently when serving heterogeneous consumers by use of data-analytics programs. Specifically, when facing large- and small-basket shoppers, stores would want to compete more for large-basket shoppers. Small-basket shoppers who buy some of the goods in the large basket reduce the price competition, but simultaneously result in a "subsidy" to small-basket shoppers. This subsidy is not totally offset by the reduced competition for large-basket shoppers. As a result, stores without information on shopping basket composition end up leaving money on the table. Data-analytics programs can help overcome this. Interestingly, data-analytics programs do not lead to dissipation of profits, even under competition. Indeed, the benefits are maximized if both competitors adopt such programs. We find that our results are robust relative to our assumptions on the information structure. However, shopping basket information is not sufficient to eliminate the consequences of shopping basket heterogeneity. With household information suitable for targeting consumers, a reward mechanism consisting of a fixed payment to large-basket shoppers allows stores to compete for each segment of consumers without offering a subsidy to any segment. This leads to a complete segmentation of the market. Interestingly, this reward lowers the price for—thus providing a true reward to—the large-basket shoppers.

There are several directions for future research. In our model the two supermarkets are symmetric. We know that competing supermarkets are often positioned differently, in particular with respect to the pricing format (Every Day Low Price or Hi-Lo, Lal and Rao 1997). Thus, it would be interesting to study the profit impact of pricing using information from data-analytics programs across supermarkets of different formats, under consumer basket heterogeneity. Another issue is that of cost structure, specifically of individual items on trade promotion. With trade promotions it might make sense to tie the reward to specific items, but this could diminish the ability to offer rewards based on customer type. What is the trade-off in offering rewards to customers versus tying them to products? Finally, data-analytics programs are used to offer frequency-based rewards. How might these affect the competition for consumers with heterogeneous baskets?

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Appendix

Proof of Lemmas 1–3. The proof of the characterization in Lemmas 1–3 follow from straightforward optimization of the (expected) profit of the stores with respect to their prices. Simultaneous solution of the necessary first-order conditions yields the solutions. The second-order conditions evaluated at the equilibrium solution have the desired sign.[20]

Proposition 1. *Assume* $F < F^* = c(1-3\alpha)^2\alpha/8(3-7\alpha)\cdot(4-9\alpha)$. *Then implementing a data-analytics program is a dominant strategy, and so in equilibrium both stores implement data-analytics programs.*

Proof. Fixing $l^k = 0$ and comparing firm i's expected profits from offering a data-analytics program to that when it does not offer it, we find that

$$\Delta\Pi^i_{10}(l^k=0) = \Pi^{i^*}(1,0) - \Pi^{i^*}(0,0) = \frac{c\alpha(1-3\alpha)^2}{8(3-7\alpha)(4-9\alpha)} - F. \tag{9}$$

Next, we fix $l^k = 1$ and compare firm i's expected profits from offering a data-analytics program to that when it does not offer it. In this case, we find that

$$\Delta\Pi^i_{10}(l^k=1) = \Pi^{i^*}(1,1) - \Pi^{i^*}(0,1) = \frac{c\alpha(1-3\alpha)^2}{2(3-7\alpha)(4-9\alpha)} - F. \tag{10}$$

Equations (9) and (10) together with $F < F^*$ imply that regardless of the rival store's decision the dominant strategy for each store is to implement a data-analytics program. □

Proposition 2. *Assume* $F < F^{**} = 3c\alpha(1-3\alpha)/8(4-9\alpha)$. *Then implementing a data-analytics program and offering rewards to large-basket shoppers is a dominant strategy for both stores. Equilibrium strategies are as follows:*

$$p_j^{is^*} = c, \quad \forall j,\ s=\{1,2,3\},\ i=\{A,B\},$$
$$r_1^{is^*} = c, \quad \forall s=\{1,2,3\},\ i=\{A,B\},$$

and,

$$\pi_s^i(P^{is^*}, r_1^{is^*}; l^k=1) = \frac{c}{2}, \quad \forall i\neq k,\ i,k=\{A,B\},\ \forall s=\{1,2,3\}.$$

Proof. As in the base case, there are three subgames to consider. In the subgame in which neither store implements a data-analytics program, the equilibrium pricing strategies and profits are identical to those characterized in Lemma 1. When both stores invest in data-analytics programs, store i's demand in segments 1–3 is

$$g_t^i(P^{i1}, P^{k1}) = \frac{\alpha\big(p_t^{ks} - p_t^{is} + c\big)}{2c}, \quad \forall t,\ s=\{1,2,3\},\ i\neq k,\ i,k=\{A,B\}.$$

To compute store i's demand in segment 4, suppose the state, $s=1$. The demand for any given prices and reward offered by the two stores is

$$h_{t1}^i(P^{i1}, P^{k1}) = \frac{(1-3\alpha)\big(p_1^{k1} + p_2^{k1} + r_1^{i1} - r_1^{k1} - p_1^{i1} - p_2^{i1} + c\big)}{2c}. \tag{11}$$

[20] Detailed proofs can be made available upon request.

The demands in the other states can be similarly computed. Given the demands, the profits of both the stores can be obtained. Maximizing the stores' profits with respect to p_j^{is}, $j, s = \{1, 2, 3\}$ and r_1^{is} and solving the necessary first-order conditions, we obtain

$$p_j^{is*} = c, \quad \forall\, i = \{A, B\},\ j, s = \{1, 2, 3\}, \tag{12}$$

$$r_1^{is*} = c, \quad \forall\, i \in \{A, B\},\ \forall\, s \in \{1, 2, 3\}. \tag{13}$$

The equilibrium profit in this subgame is

$$\pi_s^i(P^{is*}, r_1^{is*}; l^k = 1) = \frac{c}{2}, \quad \forall\, i \neq k,\ i, k = \{A, B\},\ \forall s = \{1, 2, 3\}. \tag{14}$$

Finally, consider the subgame in which one store invests in data-analytics but the other does not. Assume without loss of generality that store B invests in a data-analytics program but store A does not. The expected demand of store A in segments 1–3 is as defined in (2):

$$G_t^A(P^{A0}; l^B = 1) = \tfrac{1}{3}\sum_{s=1}^{3} g_t^A(P^{A0}, P^{Bs}), \quad \forall\, t = \{1, 2, 3\}.$$

Store A's demand in the type 4 consumer if state is $s = 1$:

$$h_{t1}^A(P^{A0}, P^{B1}) = \frac{(1-3\alpha)\left(p_1^{B1} + p_2^{B1} - r_1^{B1} - p_1^{A0} - p_2^{A0} + c\right)}{2c}. \tag{15}$$

$h_{ts}^A(P^{A0}, P^{Bs})$, $s = \{2, 3\}$ can be computed similarly. Because store B has a data-analytics program, it knows the true composition of the basket of type 4 consumers. In state s, $s \in \{1, 2, 3\}$, store B's market share in segments 1–3:

$$g_t^B(P^{Bs}, P^{A0}) = \frac{\alpha\left(p_t^{A0} - p_t^{Bs} + c\right)}{2c}, \quad \forall\, t, s = \{1, 2, 3\}. \tag{16}$$

Store B's market share in segment 4 if the true state is $s = 1$,

$$h_{t1}^B(P^{B1}, P^{A0}) = \frac{(1-3\alpha)\left(p_1^{A0} + p_2^{A0} + r_1^{B1} - p_1^{B1} - p_2^{B1} + c\right)}{2c}. \tag{17}$$

$h_{ts}^B(P^{Bs}, P^{A0})$, $s = \{2, 3\}$ can be similarly computed. Optimizing stores' profit functions with respect to their prices and rewards, we obtain the optimal prices and profits in this subgame:

$$p_j^{A0*} = \frac{c(2-3\alpha)}{(4-9\alpha)}, \quad \forall\, j = \{1, 2, 3\}, \tag{18}$$

$$p_j^{Bs*} = \frac{3c(1-2\alpha)}{(4-9\alpha)}, \quad \forall\, j, s = \{1, 2, 3\}, \tag{19}$$

$$r_1^{Bs*} = \frac{c}{2}, \quad \forall\, s \in \{1, 2, 3\}. \tag{20}$$

Substituting (18)–(20) in the respective profit functions we obtain

$$\pi_0^A\left(P^{A0*}, r_0^{A0*} = 0; l^B = 1, r_1^{Bs*}\right) = \frac{c(2-3\alpha)^2}{2(4-9\alpha)}, \tag{21}$$

$$\pi_s^B\left(P^{Bs*}, r_1^{Bs*}; l^A = 0, r_0^{A0*} = 0\right) = \frac{c(16 - 9\alpha(5-3\alpha))^2}{16(4-9\alpha)}, \quad \forall\, s = \{1, 2, 3\}. \tag{22}$$

Given the profits in the three subgames, it is easy to show that if $F < 3c\alpha(1-3\alpha)/8(4-9\alpha)$, then $\Delta\Pi_{10}^i(l^k = 0) > 0$. Similarly, if $F < 3c\alpha(1-3\alpha)/2(4-9\alpha)$ then $\Delta\Pi_{10}^i(l^k = 1) > 0$. Hence, if $F < F^{**} = 3c\alpha(1-3\alpha)/8(4-9\alpha)$, then implementing a data-analytics program and offering rewards to large-basket shoppers is a dominant strategy for both the stores. □

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