ONLINE INFOMEDIARIES AND PRICE DISCRIMINATION: EVIDENCE FROM THE AUTO-RETAILING SECTOR

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ABSTRACT

This paper focuses on a novel mechanism for market segmentation and price discrimination based on consumers' use of *online infomediaries*. Using the auto-retailing context as the setting for our study we address the following question: Can online infomediaries serve as a viable mechanism for market segmentation and price discrimination? We draw upon a unique and extensive dataset of consumers who report on the information they found when using online buying services (OBS) as part of their new vehicle purchase process. The analysis of the dataset shows that consumers who obtain price information pay lower prices (for the same product) while consumers who obtain product information pay higher prices. While this points to the existence of distinct consumer segments, this knowledge is of limited value without a viable mechanism that enables firms to specifically identify and target these customer-segments. Based on consumer usage patterns of OBSs, we then uncover distinct OBS clusters and empirically demonstrate that the usage of these different clusters is associated with predicted differences in consumer outcomes. We also show that the differential use of OBS clusters is systematically related to underlying consumer characteristics. We discuss the relevance of our findings for auto-dealers and manufacturers as well as for other industries where online infomediaries have established a significant presence.

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INTRODUCTION

Researchers and practitioners acknowledge that effective market segmentation is crucial for price discrimination and can play a vital role in a firm's profitability and survival (e.g., Bolton and Myers 2003). Traditionally, firms have attempted to target different categories of consumers through product versioning, coupons and rebates, bundling, and quantity discounts. A primary objective of these strategies is to identify consumers or groups of consumers with different price elasticities, to enable greater surplus-extraction. Over the years, simpler segmentation strategies based on demographic, lifestyles, and socio-economic variables have been superseded by more sophisticated benefit and need-based segmentation. With the increase in the variety of marketing channels, firms have sought to exploit differences *across* channels to segment consumers, with the underlying logic that customers self-select into channels that differ in their costs of time, travel, shopping, etc. (Anderson, Day, and Rangan 1997).

Recently, a few studies have examined differences in consumer behavior across online and offline channels. Hitt and Frei (2002) study online banking consumers and find specific unobservable characteristics that make online consumers better customers compared to their offline counterparts. Scott-Morton, Zettelmeyer, and Silva-Risso (2001a) find that individuals with lower negotiation skills are more likely to use online intermediaries, and Zettelmeyer (2000) examines how firms can exploit the differences between traditional and online channels to segment consumers by controlling the amount of information made available through alternative channels.

Although differences across online and offline channels can be useful in segmenting consumers, in several sectors such as auto-retailing, brokerages, mortgages, and insurance, the Web is rapidly emerging as *a primary* source of information. Much of this information is provided by neutral third-party online infomediaries who have established themselves as pivotal and trustworthy information sources. Thus, as consumers increasingly begin to rely on the Web to satisfy their information needs, the distinction between online and offline channels as predictors of differences in consumer characteristics is becoming moot. Acknowledging the growth of the Web, researchers have begun to focus on its role in customer segmentation. For example, a few studies attempt to segment online consumers based on observable information seeking behaviors, such as sites visited and time spent. Forsyth, Lavoie, and McGuire (2000) find that “simplifiers” who look for readily available product information are the most profitable segment and account for 50% of all online transactions. In contrast, “bargainers” are primarily concerned with finding a good price and maintaining control over their transactions. A related study by Rozanski, Bollman, and Lipman (2001, p.3) identifies “occasionalization” or “how online consumers behave during different Internet sessions”, as good predictors of consumer segments. Although these studies do not offer tangible guidelines for firms to exploit underlying differences in online behaviors, in light of the growing importance of the Internet as an information source, they nevertheless highlight the need to understand the nature of online segmentation strategies that can complement existing strategies in conventional channels.

This paper focuses on a novel mechanism for market segmentation and price discrimination based on consumers’ use of *online infomediaries*. Online infomediaries (also known as Online Buying Services; OBS), such as Auto-By-Tel, LendingTree, and Insweb.com, have established themselves as pivotal players in the value chains of multiple sectors including automobiles, financial services, insurance, and real estate. The array of services provided by these firms, ranging from simple information provisioning to the facilitation and brokering of transactions with other companies, is well documented. What is not addressed in the literature, however, is the potential role of online infomediaries in market segmentation and price discrimination. To the extent that consumers differ in their information seeking behaviors and online infomediaries differ in the types of information they provide, focusing on consumers’ use of these infomediaries offers a rich and novel opportunity for understanding online market segmentation through consumer self-selection.

Using the auto-retailing context as the setting for our study, we address the following question: *Can online infomediaries serve as a viable mechanism for market segmentation and price discrimination*? We begin with a simple analytical model that investigates the implications of providing different types of information on the price paid by consumers and motivates our empirical analyses. We draw upon a unique and extensive dataset of over 16,000 consumers who obtain price and product-related information from online information sources in their new vehicle purchase process to test the propositions following from our analytical model. These initial findings reinforce the results of the analytical model: they indicate the existence of consumer segments that not only seek different types of information but also pay different prices for the same product, a likely reflection of their underlying price sensitivities. However, the key question that remains unanswered is how to identify and target these customer segments to develop actionable marketing strategies.

Based on consumers' OBS-usage patterns we identify distinct clusters of OBSs and show that usage of these clusters, each of which provides a different mix of information, leads to significant differences in consumer outcomes. We also find that the observed behavioral choices—i.e., consumers' use of OBS clusters—are related to underlying differences in consumer characteristics. These findings help establish a very crucial linkage—between consumers' usage of different types of online infomediaries and the prices paid by them for identical purchases. This mapping provides valuable insights that can potentially help sellers segment consumers based on their OBS-usage patterns. We discuss the relevance of our findings for retailers who obtain referrals from these different online infomediaries, as well as for manufacturers.

This study makes several important contributions. It is among the first to characterize the information provision strategies of online auto-retailing infomediaries and to investigate their potential as a mechanism for traditional firms to implement segmentation and price discrimination strategies. While prior research has largely ignored distinctions among different online infomediaries, we show that there exist theoretically meaningful and empirically robust clusters of OBS firms that are clearly demarcated in terms of consumer usage patterns, and further differentiated on the type of information provided. A key implication then is that as long as the cost of providing different categories of information is low, online infomediaries can serve as not only an effective but also an efficient market segmentation and price discrimination mechanism for dealers. Our findings also have some interesting implications for dealers' partnerships with online infomediaries. In contrast to Chen, Iyer, and Padmanabhan (2002) who showed that an *exclusive* referral arrangement between an online infomediary and one of the many competing traditional dealers in a given geographical area is optimal, our study suggests that when choosing among several competing online infomediaries a traditional dealer can benefit from using these different categories of infomediaries as *complementary* referral mechanisms.

The rest of the paper is organized as follows. The following section describes the different types of infomediaries and examines the impact of their information provision strategies on consumer outcomes. We then provide a brief description of the online auto-retailing landscape and describe the data and measures used in the study. Following the preliminary analyses, we empirically identify distinct clusters of online infomediaries based on consumer usage patterns and present the predictions relating the use of these clusters on consumer outcomes along with the associated empirical analysis and results. We then discuss the findings, their managerial implications, and the limitations of our study. The final section contains concluding remarks.

ONLINE INFOMEDIARIES AND THEIR IMPACTS

Online infomediaries position themselves by making strategic choices about the type of information they will provide. Two varieties of infomediaries have been identified by earlier studies—those that focus primarily on *price* and those that also provide significant *product related* information. With respect to price information, some prior research has examined outcomes associated with price comparison engines or "shopbots." For instance, Baye and Morgan (2001) find that establishing a market for price information leads to more competitive pricing by firms. A subsequent study by Baye, Morgan, and Scholten (2003) finds that consumers using a price infomediary (Shopper.com) save an average of 16% on purchases compared with non-users. Smith and Brynjolfsson (2001), in their analysis of consumer choice data from another price infomediary

(Dealtime.com), find similar results of lower average prices, but their findings suggest that retailers use a number of strategic options to mitigate price pressures. Studies of auto-retailing infomediaries (Chen, Iyer, and Padmanabhan 2002) uncover similar dynamics, finding that online referral intermediaries lead to greater price competition among traditional dealers and improve consumer welfare by transferring surplus from competing dealers to online consumers. As might be expected, most of these studies focus on the implications of price transparency enabled by these infomediaries[1], and their findings echo the conventional wisdom that electronic markets lead to lower average prices and improved efficiency.

While the implications of price information availability are relatively straightforward, the impact of product information on consumer welfare is more complex. For instance, studies by Alba et al. (1997) and Lynch and Ariely (2000) find that reducing product related search costs can increase consumers' willingness to pay. Studies of information provided by certification intermediaries (Lizzeri 1999) and expert reviewers (Eliashberg, and Shugan 1997) also suggest that such information can have a positive impact on sellers' revenues. Grossman and Shapiro (1984) find that informative advertising about product characteristics can lead to greater substitutability between horizontally differentiated products and lower prices. Thus, depending on the specifics of the context (e.g., von der Fehr and Stevik 1998) and more importantly, on whether information accentuates or attenuates the differences, the availability of product information could lead to higher or lower prices for consumers. Given the focus of infomediaries on providing price and product information it is important to understand the impact of each of these information categories on consumer outcomes. We begin our investigation with a stylized analytical model that explores the ramifications of different types of information made available to consumers.

Impact of Price-Related Information

Consumers typically seek information on multiple product attributes during the purchase process. In the case of high involvement and highly differentiated products, such as cars, comparative *price* (rather than product) information can be hard to obtain. Consider a situation where all consumers have full access to information on the attributes of competing products; however not all consumers have access to price information. To examine the impact of *an increase in the availability of price information*, consider the extreme case where there is no price information and all consumers are uninformed about the relative prices of competing offerings. Also, consumers are unable to infer prices from information about the product offerings. Lacking additional information about relative prices charged by the firms, all uninformed consumers have symmetric expectations about the firms' prices. In other words, uninformed consumers have no *a priori* expectations that one seller charges a higher/lower price than the other. Since consumers have product-related information, lacking information about relative prices they purchase the product offering the best fit. Consequently, each firm acts as a monopolist in its market, as no consumer switches firms.

Now, let a fraction θ of consumers have costless access to the prices charged by the two firms, while the rest ($1 - \theta$) are uninformed about firms' prices. It is easy to see the role of increasing access to price information. When some consumers are informed of prices (i.e., $\theta > 0$), in making their choice the informed segment takes into account not only the relative fit of the two products, but also their relative prices. With increasing availability to price information, θ increases and firms increasingly compete on prices for these "informed" consumers. Thus:

Proposition 1: *As consumers obtain price information about competing offerings the average price paid by consumers is lower in equilibrium.*

Impact of Product-Related Information

Third-party infomediaries typically provide information about the characteristics of competing products and enable consumers to compare competing offerings. Unlike comparison advertising that attempts to reduce the value of competing brands relative to the advertised brand (Aluf and Shy 2001), information provided by third-party infomediaries might not always increase demand for a single firm; rather such information allows consumers to learn about their personal "fit" with a product. Consequently, such unbiased information enables some consumers to learn that a particular seller's offering is not suited to their tastes while enabling others to realize that it is. More precisely, product information in this setting enables the population of consumers to discover their true underlying distribution of preferences, leading to better fit. Thus, the impact of product information provided by neutral third-party infomediaries leads to an increase in the variance (represented by $1/\alpha$ in the Proof for Proposition 2, Appendix A) of the distribution of consumer preferences, while the mean of the altered distributions remain the same—i.e., the distribution of consumer preferences *ex ante* and *ex post* differ in mean-preserving spreads[2].

The assumption of increasing variance (increasing $1/\alpha$) in consumer preferences resulting from product-related information is particularly suited to complex and infrequently-purchased products such as automobiles, where consumers are, *a priori*, unaware of their true preferences on several dimensions critical to their purchase decision. Specifically, for the case of products with *real* differentiation, providing information about the characteristics of the competing products is more likely to increase dispersion of consumer preferences[3]. In other words, a more heterogeneous distribution (higher values of $1/\alpha$) is obtained by relocating consumers from the center of a homogeneous distribution (smaller values of $1/\alpha$) more towards the tails. As consumers become more sensitive to the differences between the competing products—i.e., as they move closer to one of the competing offerings—the market becomes less competitive. Thus, given the availability of price information, providing comparative product information about competing offerings has the same effect as increasing product differentiation, leading to greater market power (higher prices) for the competing firms.

Proposition 2: *As consumers obtain product-related information, the average price paid by consumers is higher in equilibrium.*

In summary, we have asserted that differential availability of price and product information will be systematically related to the prices consumers pay. Appendix A describes a simple analytical model that captures the impacts of increasing price and product-related information, and contains the proofs for Propositions 1 and 2. As a next step we seek to test these broad propositions, grounding our preliminary analyses in the specific context of auto-retailing, described below. This preliminary analysis then forms the basis for contextualized hypotheses that yield implications for segmentation strategies linked to infomediary usage.

RESEARCH CONTEXT AND DATA DESCRIPTION

Estimated at around a trillion dollars a year, auto-retailing is the biggest retailing sector in the US. Dominated by over 22,600 new car dealerships, the auto-retailing sector is unique in several respects. There is no national brand, the 10 largest dealers enjoy less than a 6% market share, and sales are largely localized. The presence of franchise laws serve to strengthen the position of dealers in the retail value chain. Unlike commodity items, significant differences exist among cars in terms of performance and features as well as in the pricing strategies of dealers—making the car buying process a complex decision for most consumers. The need for finance, insurance, warranties, spare parts and service, among others, add to this complexity. Given that search and comparison-shopping are costly for consumers, dealers typically resort to aggressive sales tactics to close deals with consumers visiting their dealerships.

With the advent of the World Wide Web, several online intermediaries have emerged to improve overall market efficiency through better information availability[4]. Independent *Online Buying Services* (OBS), the pioneers of online automotive retailing, perform several functions. Primary among them is providing an alternate channel for dealers to acquire customers, or acting as a *referral intermediary*. In addition to their role as referral intermediaries, OBSs also serve as *infomediaries* by providing information relating to various facets of the purchase. For instance, OBSs such as Autobytel facilitate side-by-side comparisons of different makes and models, provide pricing information, and offer financing and insurance services to consumers—none of which are easily available in the traditional setting. The number of online auto-retailing infomediaries has risen significantly in the past five years and, given the plethora of services and information offered by various online intermediaries, there appears to be some differentiation in their value-proposition for consumers or for dealers[5].

Data and Measures

We use an extensive secondary data set constructed from a survey of new vehicle purchasers conducted by a leading market research organization. This dataset has a number of distinguishing features. It is representative of the overall US automobile consumer population, and captures consumer *demographics*, *psychographics*, as well as *online information sources used* by consumers in their purchase process. The results reported in this paper reflect data collected for 2003-04 new vehicle purchases. In this market research survey, the sample was randomly selected based on registration data and the sampling process was designed via quota sampling and a sales-weighting scheme to accurately reflect the overall market for new cars. Two versions of the questionnaire were used with a different order of response elicitation in order to check for bias due to respondent fatigue or programmed responses. A response rate of about 24% was achieved for 116,317 surveys mailed out. The dataset consists of both traditional consumers as well as consumers who used the Internet as part of their purchase process. We restrict our analyses here to consumers who reported using Internet information sources to aid their automobile purchase process. In addition, to adequately control for vehicle fixed effects, the analysis is based on the 140 most popular vehicles purchased. Out of a total sample of 26,361 consumers, 16,188 reported using one or more of 30 different online infomediaries (OBSs) as part of their auto-purchase process.

Consumers answered questions relating to their *usage of specific online OBSs*, *information found online*, *price paid* (excluding tax, license, and trade-in fees), *vehicle choice*, and *satisfaction*. They indicated which sites they had visited from a list of the top 30 auto-related OBSs, and answered a set of questions about the specific type of information they found online. Of these, five items represented *price-related information* (for example, “Information about rebates and special offers”) and three items represented *product-related information* (for example, “Reliability ratings of vehicles”). These measures indicate good convergent validity (α_{price}= 0.83 , $\alpha_{product}$= 0.84) and discriminant validity for product and price dimensions (see Appendix B for factor structure).

Various individual characteristics used as controls in the analysis include consumer demographics, psychographics, internet usage, and technical competence measures. Consumer demographics measures included race, gender, age, education, and income. Price sensitivity and Involvement with the product are two key psychographic dimensions (related to consumers' utility for information) that capture the value consumers place on prices and product-choice respectively (Laurent and Kapferer 1985; Nunnally and Bernstein 1994; Zettelmeyer, Scott Morton, and Silva-Risso 2004). These were measured through items that were indicated by consumers as reflecting their valued attitudes. Involvement was assessed through responses to items such as "I want a vehicle that stands out from the crowd", and price sensitivity was measured through responses to items such as "I will shop as many dealers as it takes to get the absolute lowest price". Measures of psychographics traits of involvement and price sensitivity indicate convergent validity ($\alpha_{involvement}$= 0.77, α_{price}= 0.62) and discriminant validity (see Appendix B for factor structure). Descriptive statistics and a list of all measures are provided in Appendix B.

PRELIMINARY EMPIRICAL ANALYSIS

Our preliminary analysis tests propositions 1 and 2 by examining the relationship between the *type of information* obtained by the consumer and the resulting price paid, controlling for *individual* (demographics, psychographics, internet usage, and competence) and *vehicle* characteristics. We account for the possibility that the information obtained may itself be driven by consumer characteristics through structural estimation. The three-stage least squares (3SLS) systems estimator is used to derive the parameters of the full system because endogenous variables (information found) in the first two equations of the model are used as explanatory variables for price paid. Further, there is a possibility of correlation among error terms across regression equations as the same unobserved variables may affect both product and price information retrieval. We control for vehicle characteristics by coding vehicle/model/trim information using the vehicle identification number (VIN). The specific system of equations tested is the following:

(1) $$\textit{Found Price Info} = \beta_{01} + \beta_{04\text{-}14}(\textit{Indiv Controls}) + \varepsilon$$

(2) $$\textit{Found Product Info} = \beta_{01} + \beta_{04\text{-}14}(\textit{Indiv Controls}) + \varepsilon$$

(3) $$\textit{Price Paid} = \beta_{01} + \beta_{02}(\textit{Found Price Info}) + \beta_{03}(\textit{Found Product Info}) + \beta_{04\text{-}14}(\textit{Indiv Controls}) + \beta_{15\text{-}154}(\textit{Vehicle Controls}) + \varepsilon$$

Results, as shown in Table 1, support our propositions 1 and 2. Finding more price information results in the consumer paying a significantly lower price ($\beta = -0.427$, $p < 0.01$), while finding more product information results in the consumer paying a higher price ($\beta = 0.190$, $p < 0.05$) on average, for the same vehicle. Further, the analysis of information search outcomes and demographic data in the same model reveals interesting aspects of the information search and purchase process. Consumers who are more avid users of the Internet and those who have a greater technical competence are more likely to find both price as well as product information. In addition, consumer characteristics which are typically difficult to assess (such as psychographics and education) influence their information search behavior. Our tests of the impact of finding price and product information (Propositions 1 and 2) imply that finding information mediates the effect of individual characteristics on price paid. In addition to search competency and effort, demographics such as race, education, and income, as well as the psychographic dimensions of involvement are found to affect information found online (see table 1). These findings suggest that price differences linked to demographics may be attenuated to some extent if the mediating role of finding information is taken into account.

INSERT TABLE 1 HERE

These results are based solely on consumers' responses about the *type of information* (price or product-related) they obtained in their search process, *irrespective* of the information sources used in their search process. Thus, although the findings point to the possibility of consumer segments (those that seek price information and those that seek product-related information) with significantly different prices paid for the same product, the findings *per se*, are not of much use to firms unless there is a viable mechanism that enables them to specifically identify and target these segments. *Given that different OBSs provide different types of* *information, a natural question that arises in this context is whether consumers' usage of OBSs can be used as a viable mechanism to identify consumer segments who pay different prices for identical products.* To answer this question, we examine consumers' OBS-usage patterns and their consequences in greater detail.

CHARACTERIZING OBSs AND CONSUMER OUTCOMES

As reviewed earlier, OBSs in the auto retailing sector offer a wide variety of information that, on the surface, appears seemingly undifferentiated. In our empirical analysis, we first explore if there are any systematic patterns of information provision that may be used to classify OBSs into clusters. Next, building on prior research and the analytical model, we develop predictions relating OBS-cluster usage to three key outcomes—*price*, *vehicle choice*, and *satisfaction*. Following this, we show that OBS cluster usage is associated with specific consumer characteristics (such as demographic and psychographic variables) that help in making segmentation based on OBS use actionable.

Consumer Usage Patterns and OBS Clusters

Prior research suggests that consumers differ in their preferences for different information categories due to heterogeneity in the outcomes they value (Furse, Punj, and Stewart 1984; Olshavsky and Wymer 1995). These differences in information needs trigger information-seeking behavior based on the expected utility of information search (Belkin and Croft 1992). Patterns of information-seeking behavior, therefore, can be used to characterize how consumers use the different OBSs. Our dataset captures the use of 30 major OBSs by consumers, enabling us to uncover *distinct* infomediary categories as revealed by consumers' usage patterns. The use of a combination of OBSs by the *same* consumer provides evidence that the OBSs satisfy similar categories of information needs. Thus, aggregating pair-wise usage of OBSs over the population of consumers serves as an objective indicator of how close or far apart the two OBSs are in terms of the information needs they satisfy.

Consumers typically visit more than one OBS (sample average = 1.67, s.d. = 2.34), and pair-wise analysis of OBS usage allows us to examine if particular pairs of OBSs are used together by more (fewer) consumers than would be expected if selected at random. Let p_i be the probability of a randomly selected consumer visiting OBS_i. The expected value of p_i is given by the number of consumers visiting OBS_i as a proportion of the total number of consumers in the dataset. Now consider a pair of OBSs, OBS_i and OBS_j. Then, $p_i{}^*p_j$ is the *expected* probability of joint visits under conditions of independence—i.e., when the choice of a particular OBS is independent of the consumer's choice of another OBS. Let p_{ij} be the *observed* probability of a consumer visiting both OBS_i and OBS_j. The difference between p_{ij} and $p_i{}^*p_j$ represents the extent to which visits to a pair of OBSs are more or less than what would be expected based on the likelihood of independent visits. We obtain the observed and expected pair-wise probabilities from count data indicating the proportion of consumers visiting each respective OBS and each OBS pair. We use the Chi-square distance metric which is a square-root of the chi-square statistic $\left[\frac{(observed - expected)^2}{expected}\right]$ as a measure of proximity among OBS pairs. This represents the degree to which consumers are (un)likely to use the two OBSs together. The distance metric is calculated for each pair of OBSs resulting in 30 X 29 combinations.

We then use Multi-dimensional scaling (MDS) to map each OBS onto spatial coordinates that are consistent with the pair-wise measures[6]. MDS assigns a specific location in Euclidean space to every OBS such that the distance between every pair of OBS in Euclidean space matches the pair-wise distance matrix as closely as possible. The MDS plot (see Figure 1) indicates that there are *three* distinct groups of OBSs. OBSs *within* a group (*proximal*) are used *together more* when compared to those *across* groups (*distant*). The position vectors from MDS (three dimensions for each OBS — X, Y, and Z coordinates) are then used as inputs to the cluster analysis procedures described next.

INSERT FIGURE 1 HERE

We use a two-step cluster analysis approach with complementary methods to determine cluster structure. Cases (each case corresponding to an OBS) are clustered, rather than variables (spatial coordinates). Following recommendations from past work (e.g., Ketchen and Shook 1996), we use a hierarchical agglomerative method to produce centroid estimates and determine the appropriate numbers of clusters based on the MDS coordinates. Ward's (1963) minimum variance method is used as it maximizes inter-cluster differences, tends to produce clusters of relatively equal size, and is relatively insensitive to outliers (e.g., Jobson 1992). The dendogram indicates a three-cluster solution with the group centroids being clearly separated. These three distinct clusters are interpretable and map to the MDS visualization. K-means clustering, which uses an iterative algorithm to minimize within-cluster and maximize between-cluster distances, was used to confirm these clusters (Sireci, Robin, and Patelis 1999). Further, we conducted stability tests by repeating the MDS analysis and clustering for two sub-samples with each consisting of a random half of the observations.

The three distinct OBS clusters uncovered empirically confirm distinct OBS-usage patterns. Cluster 1 consists of OBSs such as Edmunds, Autobytel, Kelley Blue Book, etc., while Cluster 2 consists of OBSs such as Motor Trend Online, Car and Driver, Road and Track Online, etc. Cluster 3 consists of OBSs such as Lycos Autos, Netscape Autos, Yahoo! Autos, etc.

Next, we examine if using the different OBS clusters, for simplicity referred to hereafter as cluster use, results in differences in the amount of *product* or *price* information obtained by consumers. To indicate cluster usage, we associate each case in the dataset (representing a single consumer) with three dichotomous variables representing whether or not a consumer used cluster 1, cluster 2, or cluster 3. As a result, while cluster membership for an OBS is an exclusive relationship, individuals may use more than one cluster. We test this relationship between cluster use and the level of product and price information obtained (found) using a Seemingly Unrelated Regression Estimation (SURE) model. We control for consumer (demographics, psychographics, internet usage, and competence) characteristics to ensure that the results are directly attributable to the use of the clusters. The system of equations tested is:

$$(4) \quad \textit{Found Product Info} = \beta_{01} + \beta_{02}(\textit{Cluster 1 Use}) + \beta_{03}(\textit{Cluster 2 Use}) + \beta_{04}(\textit{Cluster 3 Use}) + \beta_{05\text{-}15}(\textit{Indiv Controls}) + \varepsilon$$

$$(5) \quad \textit{Found Price Info} = \beta_{01} + \beta_{02}(\textit{Cluster 1 Use}) + \beta_{03}(\textit{Cluster 2 Use}) + \beta_{04}(\textit{Cluster 3 Use}) + \beta_{05\text{-}15}(\textit{Indiv Controls}) + \varepsilon$$

INSERT TABLE 2 HERE

Table 2 summarizes the results of the model, which indicates that using cluster 1 results in consumers finding *more price information* than clusters 2 or 3; using cluster 2 results in consumers finding *more product information* than clusters 1 or 3; and using cluster 3 results in consumers finding *less product and price information* than clusters 1 or 2. These significant differences across clusters are also confirmed using a multivariate analysis of variance (MANOVA). This empirical analysis of the relationship between cluster usage and information found, along with a content analysis of the OBS sites contained in each cluster, suggests that prospective buyers perceive clusters 1 and 2 as *price-OBS* and *product-OBS*, respectively. It is important to note that the OBSs themselves might not be positioned (or branded) as “price-OBS” or “product-OBS”; we use these terms simply to denote the type of information that consumers are more likely to find when using these OBS clusters.

Unlike clusters 1 and 2 (*price-OBS* and *product-OBS)* whose users find focused information on specific dimensions of interest, cluster 3 comprises of sites belonging to *portals* such as AOL, Yahoo!, and Netscape. These *portals* typically provide a broad array of information services that, as a result, may be of lower quality and result in less information. Interestingly, although the price and product-OBS categories were expected based on prior research and *a priori* arguments, the existence of generalist portal sites as a third category that leverages captive consumer relationships, represents a different positioning strategy for an OBS.

The Outcomes of OBS Cluster Usage

We examine the price paid, vehicle choice, and satisfaction with online search, as outcomes related to the use of OBSs. As noted before, based on the information that consumers are likely to find, we label price-comparison OBSs in Cluster 1 as *price-OBS* and product-comparison OBSs in Cluster 2 as *product-OBS*. Given this differentiation in information found by consumers using these different clusters, it follows from our earlier analysis that consumers would experience different outcomes depending on the type of OBS they use in their purchase process. This leads to our predictions regarding the impact of the different OBS categories[7]:

H1: *Consumers using price-OBS will pay a lower price on average (for the same vehicle) than other consumers.*

H2: *Consumers using product-OBS will pay a higher price on average (for the same vehicle) than other consumers.*

In addition, we also expect the usage of product-OBS to enable consumers to find offerings that better fit their preferences. The logic underlying this is that, while the availability of price information would have an impact on vehicle choice, the focus on price as the primary criteria of choice constraints the available alternatives. However, given the highly differentiated nature of the product, product information would have a greater impact on a consumer's vehicle choice, making it more likely for the consumer to change her initial vehicle choice. Thus, we hypothesize that:

H3: *Users of product-OBS will be more likely than users of price-OBS to change their vehicle choice as a consequence of obtaining information from these OBSs.*

As argued earlier, price-OBS create value for consumers by helping them find better prices, and product-OBS create value by helping consumers find products that match their preferences on specific attributes. Both of these outcomes should enhance consumer satisfaction. Therefore, the impact of OBS usage on consumer satisfaction is likely to be influenced by consumer outcomes related to price and vehicle choice.

H4: *Consumers that pay lower prices or alter their vehicle choice will be more satisfied with the online search process than the average consumer.*

Empirical Findings

As before, we use a SURE (Seemingly Unrelated Regressions) empirical specification to test the effects of OBS cluster use on consumer outcomes with the different consumer outcomes as dependent variables and consumers' usage of price-OBS, product-OBS, or portals as independent variables. We control for vehicle (make, model, and trim) and consumer (demographics, psychographics, internet usage, and competence) characteristics to ensure that the results are *directly related to the use of the clusters* and are not an artifact of consumer traits or vehicle-specific factors. The system of equations tested is:

(6) $\text{Price Paid} = \beta_{01} + \beta_{02}(\text{Portal-Cluster Use}) + \beta_{03}(\text{Product-Cluster Use}) + \beta_{04}(\text{Price-Cluster Use}) + \beta_{05\text{-}15}(\text{Individual Controls}) + \beta_{16\text{-}155}(\text{Vehicle Controls}) + \varepsilon$

(7) $\text{Vehicle Choice} = \beta_{01'} + \beta_{02'}(\text{Portal-Cluster Use}) + \beta_{03'}(\text{Product-Cluster Use}) + \beta_{04'}(\text{Price-Cluster Use}) + \beta_{05'\text{-}15'}(\text{Individual Controls}) + \beta_{16'\text{-}155'}(\text{Vehicle Controls}) + \varepsilon$

(8) $\text{Satisfaction} = \beta_{01''} + \beta_{02''}(\text{Portal-Cluster Use}) + \beta_{03''}(\text{Product-Cluster Use}) + \beta_{04''}(\text{Price-Cluster Use}) + \beta_{05\text{-}15''}(\text{Individual Controls}) + \beta_{16\text{-}155''}(\text{Vehicle Controls}) + \beta_{156''}(\text{Price Paid}) + \beta_{157''}(\text{Vehicle Choice}) + \varepsilon$

INSERT TABLE 3 HERE

Results, shown in Table 3, confirm that consumers experience significantly different outcomes depending on the OBS cluster they use. Consumers using the *price-OBS* cluster pay a significantly lower price for the same vehicle, supporting H1. Consumers using the *product-OBS* cluster pay a significantly higher price than price-OBS consumers for the same vehicle[8]. However, the differences in prices paid by the product-OBS and price-OBS consumers in Table 3 are not as strong as those reported in Table 1. Consumers who obtain an additional unit of price-related information pay an average of about $854 less for the same vehicle (P1), while those obtaining an additional unit of product-related information pay an average of about $633 more for the average car (P2). While this potential for price discrimination is not perfectly captured by consumers' OBS usage (Table 3), we find that consumers using price-OBS cluster tend to pay approximately $404 less than the average online consumer (H1)[9]. This is attributable to the fact that although we classify the OBSs as *price-OBS* and *product-OBS*, most OBSs in these clusters provide a *mix* of the different types of information. While OBSs may differ in their relative emphasis of providing price versus product information, the availability of a mix of information is likely to attenuate the strength of the results in Table 3.

In H3 we argue that consumers using the *product-OBS* cluster are more likely to alter their initial choice of make and model after visiting the OBSs providing product-related information. Our results confirm this hypothesis and reinforce our modeling assumptions that product information yields a better "fit." Users of product-OBS are 10.6% more likely to change their vehicle choice compared to the average consumer. In contrast, portal-cluster consumers are least likely to alter their vehicle choice, while price-cluster consumers fall in between these extremes. Since, our measure of vehicle-choice impact was a three-point scale we estimated the model through ordered probit analysis as well, which yielded the same results.

Consistent with H4 we find that consumers whose vehicle choices were affected by the acquisition of online information are likely to be more satisfied with the online information search process. On the other hand, we find that consumers who pay a lower price are not significantly more satisfied than other consumers. Even after controlling for price paid as well as impact on vehicle choice, we find a direct impact of price-OBS usage on satisfaction. As shown in Table 3, the use of product-OBS increases satisfaction by 1.8% while the use of price-OBS OBSs increases satisfaction by 7.9%.

Consumer Characteristics and OBS-Cluster Usage

Recall that a key objective of this study was to understand how firms can effectively identify consumer segments based on their use of online infomediaries. To accomplish this, we conduct a *post-hoc* analysis to examine if OBS-cluster usage is associated with significant differences in consumer characteristics. We use a generalized linear model (GLM) that combines regression analysis and analysis of variance for multiple dependent variables by the factor variables (OBS usage cluster membership) and covariates. Using this general linear model procedure, we test the effects of factor variables on the means of various groupings of a joint distribution of dependent variables. GLM transforms the categorical variables into sets of indicator variables and calculates parameters using IWLS (iterative weighted least squares). Table 4 presents the results of testing the following equation:

(9) (Age, Race, Gender, Education, Income, Technical competence, Internet usage, Involvement, Price sensitivity) = f (Price cluster use, Product cluster use, Portal cluster use)

INSERT TABLE 4 HERE

The results (Table 4) show that consumers using OBSs belonging to different clusters differ significantly in their psychographic and demographic profiles. In particular, we find that price and product cluster consumers are technically more sophisticated as indicated by technical competence, and are more avid users of the Internet than portal consumers. Portal consumers are also significantly different from price and product-cluster consumers in their demographics as indicated by race, age, education, and income. Specifically, portal consumers tend to be younger, non-white, less educated, and have lower income. It is noteworthy that past research has identified these demographic categories as being more susceptible to discrimination by dealers in physical settings (Ayres and Seigelman 1995; Scott Morton, Zettelmeyer, and Silva-Risso 2001a). The lack of significant differences in the demographics of price and product-cluster consumers further suggests that differences in information search behavior are more related to differences in their psychographic profiles than demographics.

DISCUSSION AND IMPLICATIONS

Our goal in this paper was to investigate the role of online infomediaries in market segmentation and price discrimination in the auto-retailing context. In contrast to prior work that has largely overlooked the distinction between the various types of infomediaries, our findings show that auto-retailing infomediaries fall into distinct categories on the basis of consumer-usage patterns–price, product, and portal clusters. A natural question that arises in this context then is: what is the impact of using the different types of infomediaries? In addition to the differences in the prices paid by consumers using the different OBS clusters, we find that consumers that use product-OBS revise their vehicle (make and model) preferences, suggesting that product-OBS add value by helping consumers make a better product choice. This is also supported by our finding of improved satisfaction for these consumers. While price-OBS usage is less likely to affect the vehicle choice of consumers,

consumers using price-OBSs pay a significantly lower price compared to other consumers. Consumers using portals pay higher prices compared to consumers using price-OBS, and they are less satisfied with their outcomes than consumers using product-OBS.

Our results also indicate that even after controlling for price and vehicle choice impact, usage of price cluster OBSs has a direct impact on consumer satisfaction. This suggests that there may be other benefits from using price OBS not captured by these two outcomes. Obtaining price information, for instance, may save consumers the costs of physical visits to and unpleasant negotiations with dealers. To verify this, we performed *post-hoc* tests examining the number of reported physical dealer visits. These results show that price cluster OBS consumers tend to visit significantly fewer physical dealers ($p < 0.001$). Both product and portal cluster consumers visit more physical dealers than the average online consumer, with portal consumers making the most visits. It is likely that while portal consumers visit additional dealers to compensate for the inability to find price and product information online, product cluster consumers, who are generally more involved with the purchase, may have a greater need for physical stimuli not adequately obtained through the use of the Internet.

In summary, both price as well as product-OBS clusters improve consumer welfare—the former through lower prices and the latter through a better product fit. Portal OBSs appear to contribute the least to consumer welfare as their users pay a higher price despite a lower product fit. It is important to note that the impact on consumer outcomes is *after* controlling for consumer psychographics (price sensitivity and involvement) and demographics. This shows that in addition to individual differences, the outcome is a result of systematic differences in OBS usage by consumers.

INSERT TABLE 5 HERE

The differences in consumer outcomes highlighted above point to a low-cost mechanism to implement price discrimination to complement existing strategies. In particular, the users of these OBS-clusters pay different prices for the same vehicle, suggesting the potential role of these infomediaries in segmentation and price discrimination[10]. While this finding is actionable in itself, these OBS-usage patterns are also linked to systematic differences in consumer characteristics. The average portal user is likely to be more vulnerable to discrimination in conventional channels. Also, consumers using price and product-OBS clusters are not significantly different on demographics. Although differences in demographics characteristics are usually more easily observable by sellers, attitudinal differences as revealed by psychographics are less apparent. This makes our findings of the effectiveness of using OBS clusters for segmentation and price discrimination more compelling.

Prior to discussing the implications of the results, it is important to acknowledge the limitations of this work. First, we are limited by the fact that we rely on secondary data collected by a third party. However, this extensive data set represents one of the largest surveys of new vehicle buyers, and is representative of the US new-vehicle market, and the measures used possess good psychometric properties. Second, there is a possibility of common methods bias as the data was collected through a single survey instrument. This is mitigated by having each response elicited through new vehicle registrations and tied to an objectively verified purchase. We also conducted Harmon's single factor test (Podsakoff and Organ 1986) on the perceptual indicators collected through the survey and obtained multiple factors with eigenvalues greater than 1, with the largest factor accounting for less than 25% of the variance. This indicates that common methods variance is unlikely to be a major concern in testing our research models. Our price sensitivity measure has a lower than ideal reliability (α_{price}= 0.62) and future research should seek better measures for this construct. A final limitation is that we infer OBS positioning and information provision strategies based on consumer data. However, a content analysis of OBS sites and discussions with industry experts helped confirm our findings.

Implications for OBSs

Our findings have significant implications for the competitive positioning of OBSs. Although a cursory examination of the online infomediary landscape suggests undifferentiated competition with most infomediaries offering a mix of information, a more systematic analysis reveals distinct patterns of usage by online consumers. Given that consumers are clearly differentiated on their underlying needs for the different types of information, infomediaries would benefit by better highlighting their domain of specialization. As highlighted earlier, our results indicate that greater specialization and differentiation of OBS clusters to facilitate consumer self-selection would increase the effectiveness of these OBSs.

A second set of implications relates to the pricing of referral services to dealers by OBSs. Currently dealers pay a uniform referral fee for each lead irrespective of the OBS providing it. However, given the potentially higher profit margins of leads from product OBS and portals, these OBSs can charge a premium for their referral services[11]. Our results show that price and product-OBSs add significant value to the price (and product) conscious customers, respectively. They could benefit by more selectively targeting these consumers as this would improve their attractiveness to their partners (dealers) in the traditional value chain. Rather than seeking to position themselves as *information specialists*, portals should leverage their relationships with their captive customer segments. As their consumers become more tech-savvy the portals risk losing these segments to the other OBS-clusters. Our findings also have implications for the design and structure of OBS system interfaces. Clemons, Hann, and Hitt (2002) observe that product-sensitive customer segments may have a higher valuation for system interface quality compared to price-sensitive customers. In addition, given the demographic and technographic profiles of the different segments, price sensitive customers may find it easier to navigate more complex interfaces. On the other hand, portal consumers who are less tech-savvy would need more easy-to-use and interactive interfaces.

Implications for Dealers and Manufacturers

This study provides a new basis for segmenting online consumers and identifies profiles of the resulting segments. Recognition and tracking of infomediary-use promises to be an effective price discrimination mechanism. As more consumers move online, understanding systematic differences in online consumer behavior will be more important in enabling traditional supply chain members to craft appropriate segmentation and pricing strategies. Our findings suggest that OBSs in these three distinct clusters should be viewed as complements (rather than substitutes), given that the consumers referred by these different clusters not only differ in their underlying demographic and psychographic characteristics, but also in their price sensitivities.

Compared to other segmentation and price discrimination strategies such as versioning, product line extensions, or couponing, segmenting based on OBS-usage serves as an effective and robust self-selection mechanism. Using online infomediaries as segmentation mechanisms also provides managers a way to limit the negative impact of discounts and coupons on brand-equity. By restricting price promotions to the consumer segments that use price cluster infomediaries, a firm can minimize the exposure of the promotion to the more brand-sensitive segments.

While past research has mainly focused on price discrimination, this study confirms that other outcomes related to consumer fit with product attributes, as well as consumer ability to find the appropriate information, need to be considered as well. In addition to the differences in the prices they pay, these segments might also differ in the cost-to-serve as well as service and promotional responsiveness. Naturally, these consumer segments would have different levels of attractiveness for different sellers. Dealers and manufacturers can design their value propositions, marketing strategies, and resource allocation in an efficient way to deliver the most value to these different segments. For instance, the explosion of new technologies that are hard to explain and that need to be experienced by consumers, has led dealers and manufacturers to invest in "experiential events" (Boudette, 2005). Clearly, dealers and manufacturers would benefit by targeting consumers referred by product-OBS for such events. In addition, as in the case of airlines that have changed their pricing strategy from pricing flights to pricing itineraries, firms can develop pricing structures based on other characteristics (e.g., for service quality) that differentiate the two segments.

CONCLUSION

Despite significant advances in identifying analytical approaches for market segmentation, the inability to effectively implement these segmentation strategies has limited their usefulness. As noted by Moorthy (1984, p. 288) market segmentation strategies have typically been difficult to implement in practice as "*identifiable* *characteristics of consumers—demographic characteristics, mostly—may not be useful in suggesting real differences in consumer behavior—differences that a firm could use*". This paper identifies a new mechanism for segmentation of online consumers using differentiated online infomediaries. Our results show that even in online environments with abundant information and reduced search costs, consumers are differentiated on the type and extent of information they find in their vehicle purchase process. More importantly, these segments are differentiated not only in the price they pay but also, on their underlying demographic and psychographic profiles. Customer heterogeneity in information needs and retrieval, which drives their use of different online infomediary-clusters, can thus serve as a robust mechanism for segmentation and price discrimination.

Understanding the evolving role of technological channels as well as consumers' usage of emerging technologies in the purchase process is crucial. Even for firms that do not use online channels for selling their products, online channels can have a substantial impact on profitability and survival. Our study provides insights into how online infomediaries can not only benefit consumers but also offer traditional firms the potential to fine-tune their marketing strategies. An examination of the OBSs suggests that they are differentiated from each other, and the assumption implicit in prior research that treats online infomediaries as a unitary category appears questionable. Our study highlights the need to go beyond a unidimensional focus on price and understand the systematic differences among infomediaries and their impacts on market outcomes. Inevitably, this research raises more questions than it answers. As the economics of supplying price related information would be very different from that of supplying product-related information, when is it optimal for an infomediary to provide price and/or product-related information, and what are the underlying drivers of such information provision? Future research should examine these questions in depth.

Table 1

The Impact of Information Obtained on Price Paid by Consumers

Variables	Dependent Variables: Structural (3SLS) Estimation		
	Found Product Information (1)	Found Price Information (2)	Price Paid (3)
Intercept	-0.108* (0.055)	0.070 (0.051)	2.772*** (0.067)
Individual Controls			
Race (Non-White)	0.088***(0.023)	0.040$^{\psi}$ (0.022)	0.040** (0.015)
Gender	0.024 (0.016)	0.024$^{\psi}$ (0.015)	-0.024* (0.010)
Age (YOB)	0.001$^{\psi}$ (0.001)	-0.001 (0.001)	-0.001 (0.000)
Education	0.013** (0.005)	0.015** (0.005)	-0.003 (0.004)
Income	0.001 (0.000)	0.001*** (0.000)	0.000* (0.000)
Involvement	-0.004***(0.006)	0.044*** (0.006)	0.018 (0.006)
Price Sensitivity	-0.010 (0.008)	-0.003 (0.007)	-0.022 (0.005)
Internet usage	0.061***(0.013)	0.032** (0.012)	
Tech. competence	0.004***(0.001)	0.003** (0.001)	
Information Found			
Found Price Information			-0.427** (0.153)
Found Product Information			0.190* (0.096)
System Weighted R^2 = 0.87 ; $N_{(LISTWISE)}$ = 4474			

*$^{\psi}$ p <.10, * p < 0.05, ** p < 0.01, *** p < 0.001*
Unstandardized regression coefficients are shown along with standard errors
Vehicle controls not shown, are included in price-paid equation

Table 2

Information Found Explained By OBS-Cluster Used

	Dependent Variables: Structural (SURE) Estimation	
Variables	Found Product Information (4)	Found Price Information (5)
Intercept	0.067 (0.067)	0.341*** (0.067)
Cluster Usage		
Cluster 3 Use	0.062*** (0.062)	0.022** (0.195)
Cluster 2 Use	0.195*** (0.195)	0.051***(0.132)
Cluster 1 Use	0.132** (0.132)	0.159***(0.031)
Controls		
Race (Non-White)	0.031 (0.031)	-0.004 (0.001)
Gender	0.018 (0.018)	-0.016* (0.012)
Age (YOB)	0.001** (0.001)	0.000 (0.003)
Education	0.012** (0.012)	0.009** (0.002)
Income	0.003* (0.003)	0.002 (0.004)
Tech. competence	0.071*** (0.071)	0.045*** (0.000)
Internet usage	0.003** (0.003)	0.001 (0.000)
Involvement	-0.002 (0.005)	0.004 (0.004)
Price Sensitivity	-0.004 (0.005)	0.014*** (0.004)
System Weighted R^2 = 0.102		
$N_{(LISTWISE)}$ = 4980		

*$^{\psi}$ p <.10, * p < 0.05, ** p < 0.01, *** p < 0.001*
Unstandardized regression coefficients & standard errors are shown

Table 3

Consumer Outcomes Explained By OBS-Cluster Used

	Dependent Variables: Structural (SURE) Estimation		
Variables	Price Paid (6)	Vehicle Choice Impact (7)	Satisfaction (8)
Intercept	2.689*** (0.070)	-0.087 (0.086)	6.883*** (0.250)
Cluster Usage			
Portal Cluster Use	-0.009 0.009	0.044$^{\psi}$ (0.025)	-0.115$^{\psi}$ (0.063)
Product Cluster Use	-0.003 0.009	0.222*** (0.025)	0.124* (0.063)
Price Cluster Use	-0.040*** (0.009)	0.138** (0.024)	0.533*** (0.061)
Controls			
Race (Non-White)	0.025$^{\psi}$ (0.013)	0.105** (0.035)	0.135 0.087
Gender	-0.016$^{\psi}$ (0.009)	0.005 (0.025)	0.026 0.061
Age (YOB)	0.000 0.000	0.007*** (0.001)	0.013*** (0.003)
Education	-0.004 0.003	0.027*** (0.008)	0.002 (0.033)
Income	0.000 0.000	0.000$^{\psi}$ (0.000)	0.000 0.001
Tech. competence	0.003 0.007	0.086*** (0.020)	0.298*** (0.050)
Internet usage	0.002* (0.001)	0.009*** (0.002)	0.021*** (0.005)
Involvement	0.011** (0.004)	0.025* (0.010)	0.024 0.027
Price Sensitivity	-0.016*** (0.004)	0.016 0.012	0.002 0.029
Consumer Outcomes			
Price Paid			0.014 (0.030)
Vehicle Choice Impact			0.952*** (0.039)
System Weighted R^2 = 0.877; $N_{(LISTWISE)}$ = 4474			

*$^{\psi}$ p <.10, * p < 0.05, ** p < 0.01, *** p < 0.001*

Unstandardized regression coefficients & standard errors are shown; Vehicle controls not shown, are included in all equations

Table 4

Consumer Characteristics and OBS Clusters

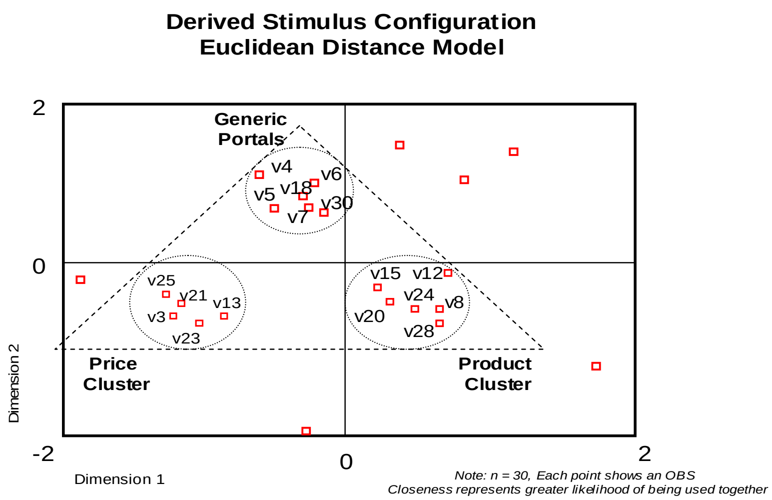
Dependent Variables : MANOVA(GLM) Estimation**										
Variables	Age (Year of Birth)	Race (0 - Non-White; 1 - White)	Gender (1 – Male, 2 – Female)	Education (8 pt scale, 1 = 8th grade or less; 8 = advanced degree)	Income (15 pt scale; 1 = Under $25K; 15 = Over $250K)	Tech. Competence (3 point scale; 1= Beginner; 3 = Advanced)	Internet Usage (Hours/Week)	Involve-ment (5 point Likert scale)	Price Sensitivity (5 point Likert scale)	N
Price Cluster Users (1)	57.390	0.104	1.336	5.993	8.532	2.243	6.614	3.291	2.810	3221
Product Cluster Users (2)	56.895	0.083	1.423	6.098	8.743	2.142	6.272	3.344	2.598	459
Portal Cluster Users (3)	55.619	0.197	1.470	5.699	7.704	1.974	6.076	3.264	2.819	1024
F(p)	7.308 (0.001)	35.464 (0.000)	32.780 (0.000)	16.773 (0.000)	22.965 (0.000)	70.301 (0.000)	3.038 (0.048)	0.789 (0.454)	8.818 (0.000)	
Scheffe* Differences	(3;1)	(3;1,2)	(1;3,2)	(3;1,2)	(3;1,2)	(3;1,2)	(3;1,2)	NS	(2;3,1)	
Overall Effect	Wilkes Lambda = 0.931 F= 16.956 P=0.000									

*: (*x*; *a*, *b*, *c*) means that group *x* is significantly different from groups *a*, *b*, and *c*.

** *The numbers shown are estimated marginal means for consumers using price, product, or portal OBS clusters, where a consumer is considered as a user of an OBS cluster if she reported using any of the OBSs in that cluster.*

FIGURE 1

Two–Dimensional Representation of OBS Positioning Based on Consumer Usage Patterns



NOTES

[1] In a study of auto-retailing infomediaries, Scott Morton et al. (2001b) find that individuals using online auto-retailing infomediaries saved approximately 2% ($450) compared to those negotiating directly with dealers. In another study of the life insurance sector, Brown and Goolsbee (2002) find that online price-comparison sites led to a 8-15% drop in term life prices, and although price dispersion increased initially, it reduced with increased Internet usage.

[2] This simplifying assumption helps maintain analytical tractability and enables us to capture the effects of product information availability in the case of complex and in-frequently purchased products with real differentiation.

[3] As noted earlier, product information could have different impacts depending on the product category and purchase context. In the case of products with perceived (rather than real) differentiation, such as branded versus generic drugs for instance, product information can reduce dispersion of consumer preferences as consumers become aware of the lack of any real differentiation between the competing products (also see Johnson and Myatt 2004).

[4] According to consumer surveys (J. D. Power and Associates 2002), 62% of all new-vehicle shoppers research their purchase online (the average consumer visits approximately 7 automotive sites) before buying.

[5] In addition to OBSs, dealers and manufacturers have established their own Web sites. However, unlike the independent online infomediaries, most have failed to establish a significant presence online.

[6] We follow a two-step approach of first using MDS and then using cluster analysis to derive segments. This approach may produce varying results if researchers fail to retain valuable information about distances in components with smaller eigen-values and due to sensitivity of results to alternative methods (Sinha and DeSarbo 1998). In this study, we confirmed the stability of our results under these varied spatial models (2 dimensions and 3 dimensions), rotational schemes, and normalizing techniques. Further, we do not interpret

the specific positions of OBSs or the dimensions – rather we are interested in groupings, which are then assessed based on consumer characteristics and outcomes.

[7] While propositions 1 and 2 are concerned with the implications of consumers obtaining more price and product information, hypotheses 1 and 2 are concerned with the outcomes of consumers' usage of different OBS types. If all consumers that seek price (product) information use pure price (product) OBS then the propositions and corresponding hypotheses H1 & H2 would be identical. However, as noted earlier, although OBSs might specialize in providing one type of information (price or product) most OBSs still tend to provide a mix of the different types of information.

[8] It is important to note that the classification of price-OBS, product-OBS and portals is not based on information obtained or consumer outcomes such as prices. It is solely based on pair-wise usage patterns. Second, the differences in prices paid are significant even after controlling for price-sensitivity and product involvement, and consumer characteristics, implying the information provision plays a significant role. Third, all OBSs supply a mix of information types (although they may focus on more than others), and consumers are not perfectly informed about OBS positioning. Finally, consumers may also be using other information sources apart from the Internet and may also engage in face-to-face negotiations.

[9] The dollar figures illustrating the impact of price and product information are based on a $20,000 car (~average for our sample) and an incremental unit of (price/product) information found by consumers.

[10] This finding is robust to structural specifications with information found as a mediator as well as the likelihood of unobserved consumer characteristics driving both OBS use and outcomes.

[11] We would like to thank Dennis Galbraith (Senior Director, Automotive Marketing Solutions, J.D. Power and Associates) for this insight.

[12] Although we use the terminology of a "fulfilled-expectations equilibrium" (for instance see, Katz and Shapiro, 1985), the prices derived in equation 1 also satisfy the requirements of a Bayesian-Nash equilibrium. (In equilibrium, uninformed consumers are correct in their beliefs about relative prices charged by both firms).

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APPENDIX A: PROOFS OF PROPOSITIONS

Given that online infomediaries provide varying combinations of product and price information, we are interested in examining the implications of such differential information being made available to consumers. We describe an analytical model that examines the implications of providing price and product-related information to consumers. In keeping with the context of this study, we are particularly interested in the impact of information provided by neutral third-party infomediaries, rather than by the firms per se. Since infomediaries in our model are passive information providers, we do not model their strategic intent.

We model a stylized duopolistic setting where identical firms A and B located at the two ends of a unit line segment (firm A located at 0, firm B located at 1) sell differentiated offerings to a unit mass of consumers. The firms in our model represent traditional dealers with differentiated offerings. As we are primarily interested in the impact of third-party information on prices, we assume that firms' locations are fixed. Consumers are utility-maximizers and each consumer is in the market for one unit of a product. Each consumer has an ideal product that gives her the highest utility and this ideal product determines her location on the unit line segment. She incurs a loss of utility when she buys a product other than her ideal one. Consumers are assumed to have a high reservation price $\check{r}$, in comparison with their total costs. High reservation prices ensure that consumers always purchase a product and the market is covered; so the problem focuses purely on the competitive aspects of the channel (Economides 1989). Consumers are distributed according to their ideal products on the unit interval by a cumulative distribution function F, and the consumer density *f*(x) is continuous, twice differentiable, and strictly log-concave. Several well-known distributions including uniform, normal, exponential, Weibull, and Beta, among others have log concave density functions (also see Bagnoli and Bergstrom 2004). For sake of simplicity we consider a symmetric distribution F. Thus, if *x* denotes a point on this interval; *f*(*x*) is the consumer density and F(*x*) is the cumulative distribution function (the probability that the variable takes a value ≤ *x*), given by $F(X) = \int_a^b f(x)dx = \Pr[a < X < b]$, where f(x) is continuous, twice differentiable, with a strictly log-concave density, and F(0) = 0, F(1) = 1.

Firms seek to maximize profits, and given their locations and the distribution of consumer preferences, firms simultaneously choose prices non-cooperatively. Without loss of generality we assume that the fixed costs and marginal costs of both firms are zero.

Consumer disutility when she buys when she buys a product other than her ideal one varies linearly with distance. The total cost incurred by a consumer when she purchases a product is the sum of the price she pays for the product and the misfit (disutility) cost. The utility that a consumer located at a distance x_i from firm A derives when purchasing from A is given by, $U_i = r - p_A - (t)x_i$, where t is the disutility per unit distance. We use this setup to analyze the impacts of increasing product as well as price information availability to consumers. To highlight the differential impacts of price and product-related information we are interested in the two extreme cases—the first where all consumers have access to full product-related information but not to price-related information; the second where consumers have access to firms' prices but lack access to product-related information. We then examine the impact of increasing access to price-related information to consumers in the first setting and the impact of increasing access to product-related information to consumers in the second setting.

Proof of Proposition 1

Let x be the location of the indifferent informed consumers. Let p_A be the price charged by firm A, p_B be firm B's price. As noted earlier, the total cost to a consumer located at distance x from A and purchasing from firm A is $p_A + tx$. Correspondingly, the cost to the consumer of purchasing from firm B is $p_B + t(1-x)$. The location of the indifferent consumer is given by, $p_A + tx = p_B + t(1-x)$; i.e., $x = \frac{p_B - p_A + t}{2t}$. A fraction θ of consumers have costless access to firms' prices, while the rest (1-θ) are uninformed about firms' prices and have symmetric expectations about the prices charged by the two firms; i.e., they expect the prices charged by both firms to be identical. All consumers are perfectly informed about the product characteristics of both firms. Then, firm A's demand from informed consumers is θF(x), and Firm B's demand is θ(1-F(x)). Firm A's (as well as Firm B's) demand from uninformed consumers is $\frac{(1-\theta)}{2}$. The profit functions of the two firms are given by, $\pi_A = p_A\left(\theta F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right) + \frac{1-\theta}{2}\right)$, and $\pi_B = p_B\left(\theta\left(1 - F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)\right) + \frac{1-\theta}{2}\right)$. Given the firms' profit functions we derive the fulfilled-expectations equilibrium prices p_A^*, and p_B^* as follows. Differentiating the profit functions with respect to prices we have,

$$\frac{\partial \pi_A}{\partial p_A} = \theta\left(F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right) - \frac{p_A f\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}{2t}\right) + \frac{1-\theta}{2}; \quad \frac{\partial \pi_B}{\partial p_B} = \theta\left(1 - F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right) - \frac{p_B f\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}{2t}\right) + \frac{1-\theta}{2}.$$

Solving for FOC, the optimal prices for the two firms are given by,

(1) $$p_A^* = 2t\frac{F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right) + \frac{(1-\theta)}{2\theta}}{f\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}; \qquad p_B^* = 2t\frac{1 - F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right) + \frac{(1-\theta)}{2\theta}}{f\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}.$$

In the case of identical firms (firms A and B are identical except for locations), and a symmetric distribution F of consumers, the firms' prices are the same in equilibrium (i.e., $p_A = p_B$). As is evident from equation 1, in the case of a symmetric distribution F, $p_A^* = p_B^*$, and thus, the uninformed consumers' expectations about the relative prices charged by the two firms are indeed fulfilled in equilibrium[12]. Also, as is evident from the expressions in (1) for optimal prices, p_A^* and p_B^* decrease as θ increases. In other words, as θ (availability of price information) increases, the proportion of informed consumers increases leading to lower prices.

Proof of Proposition 2

As earlier, to highlight the impact of product information, let us consider the case where all consumers have full access to firms' prices, i.e., assume θ = 1. The profit functions of the firms are then given by, $\pi_A = p_A F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)$, and $\pi_B = p_B\left(1 - F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)\right)$. Substituting θ = 1, in the expressions for optimal prices in (1), we have

(2) $$p_A^* = 2t\frac{F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}{f\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}; \qquad p_B^* = 2t\frac{1 - F\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}{f\left(\frac{p_B - p_A}{2t} + \frac{1}{2}\right)}.$$ -

To examine the impact of changes in product information availability, we consider a specific log-concave probability distribution, a Beta distribution. Beta distributions have been widely used to model consumer preferences as they fit empirical distributions of consumer purchases very well (Ansari et al.,1994). A uniform distribution is a special case of a Beta distribution with α1 = α2 = 1.

Let consumers preferences follow a symmetric unimodal beta distribution with shape parameters $\alpha_1 = \alpha_2 = \alpha \geq 1$. The level of heterogeneity in consumer preferences can be measured by the parameter α. The beta distribution allows us to vary the degree of heterogeneity in consumer preferences while holding constant the number of consumers in the market.

The probability density function of the beta distribution is given by $f(x)=\frac{x^{\alpha-1}(1-x)^{\alpha-1}dx}{B[\alpha,\alpha]}$, where B[$\alpha$,$\alpha$] is the beta function with, $B[\alpha,\alpha]=\int_0^1 x^{\alpha-1}(1-x)^{\alpha-1}dx$. The expected value of the beta distribution is $E[X]=\frac{1}{2}$, and its variance is $V[X]=\frac{1}{4(2\alpha+1)}$. As can be seen, the variance of a symmetric beta distribution is inversely related to α. For α >1, the higher the value of α the more peaked the distribution, and the more homogenous the consumer preferences. With identical firms and a symmetric distribution of consumers the optimal prices are,

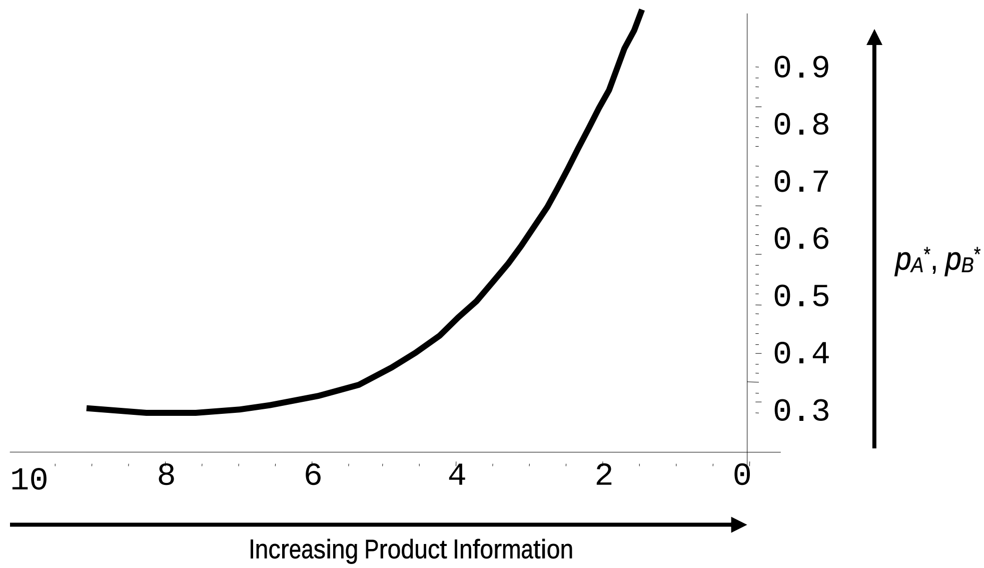
$$p_A^*=p_B^*=2t\frac{F\left(\frac{1}{2}\right)}{f\left(\frac{1}{2}\right)}, \quad \text{where} \quad F\left(\frac{1}{2}\right)=\frac{\int_0^{\frac{1}{2}} x^{\alpha-1}(1-x)^{\alpha-1}dx}{\int_0^1 x^{\alpha-1}(1-x)^{\alpha-1}dx}, \text{ and } \quad f\left(\frac{1}{2}\right)=\frac{\frac{1}{2}^{\alpha-1}\left(\frac{1}{2}\right)^{\alpha-1}dx}{\int_0^1 x^{\alpha-1}(1-x)^{\alpha-1}dx}.$$

Specifically, for a symmetric Beta distribution we have, $$p_A^*=p_B^*=2t\frac{\sqrt{\pi}\Gamma[\alpha]}{4\Gamma[\frac{1}{2}+\alpha]}.$$

When consumers have little product-related information they are indifferent to the competing offerings and make their purchase decisions solely based on the relative prices. This can be represented by a distribution with low variance (high α) with consumers being clustered toward the mean. As consumers obtain more product-related information, their preferences become well defined and consumers discover that their preferences are more closely aligned with one of competing offerings. In other words, the variance of the distribution of consumer preferences increases as consumers discover their true preferences. Thus increasing product information causes an increase in the variance (lower α) of the distribution of consumer preferences. Figure A-1 illustrates how the optimal prices vary with α.

FIGURE A-1

Optimal Prices with Product Information



APPENDIX B

TABLE B-1
CONSTRUCT OPERATIONALIZATION

Meta-Construct	Constructs	Mean	S.D.	Operationalized As
Consumer Psychographics	Involvement (Cronbach's alpha = 0.77)	3.26	1.15	Average of agreement (5 pt. scale) with statements for items corresponding to factors
	Price Sensitivity (Cronbach's Alpha = 0.62)	2.82	1.05	
Consumer Demographics	Race	0.12	0.33	White – 0, Non-White – 1
	Gender	1.38	0.49	Male – 1, Female - 2
	Age	56.12	13.27	Year of birth
	Education	5.93	1.57	8 point scale
	Income	8.27	3.71	15 point scale
Information Found	Found Product Information (Cronbach's alpha = 0.84)	0.60	0.41	Average of "Found information online" (Dichotomous scale) for items corresponding to each factor
	Found Price Information (Cronbach's alpha = 0.83)	0.69	0.29	
Search Competency and Effort	Internet Expertise	2.20	0.65	Overall level of Internet experience (3 pt. scale)
	Internet Usage	6.69	6.50	Hours per week
Outcomes	Vehicle Price Paid	2.93	1.29	Total price (excl. tax, license, trade-in)/$10K
	Satisfaction with search process	6.76	2.10	Overall experience using the Internet to research/shop for vehicle [10-pt. scale]
	Impact on Vehicle Choice	2.08	0.767	"How much of an impact did your Internet research have on…what make/model to purchase/lease." [3 pt. scale]
	Extent of Physical Dealer Visits	1.46	1.06	How many physical dealers visited to look at alternate vehicles

TABLE B-2
FACTOR ANALYSIS FOR CONSUMER PSYCHOGRAPHIC DIMENSIONS

	Involvement	Price Sensitivity
I want a vehicle that stands out from the crowd	0.856	-0.014
What you drive says a lot about you	0.832	0.027
Getting the lowest price is more important to me than finding a dealer that provides customer service	-0.005	0.677
I will shop as many dealers as it takes to get the absolute lowest price	0.037	0.754
I would gladly travel another 50 miles to buy from a dealer that could save me an additional $ 300	-0.030	0.664

TABLE B-3
FACTOR ANALYSIS FOR INFORMATION FOUND DIMENSIONS

	Found Price-Information	Found Product-Information
Dealer cost/invoice of new vehicles	0.739	-0.016
Options and features information (descriptions, prices, etc.)	0.527	-0.076
Tool to show how much dealers are discounting vehicles	0.658	-0.078
Tool to calculate MSRP with the options you want	0.644	-0.015
Information about rebates and special offers	0.656	0.055
Road test and reviews about vehicles by automotive writers	-0.096	0.706
Safety information (crash test results, etc.)	-0.002	0.830
Reliability ratings of vehicles	-0.018	0.872

TABLE B-4
PAIRWISE CORRELATION MATRIX

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
1. Race																	
2. Gender	0.02																
3. Age	0.13	0.17															
4. Education	0.01	-0.09	-0.06														
5. Income	-0.07	-0.18	-0.14	0.36													
6. First Vehicle	0.06	0.02	0.15	0.00	-0.11												
7. Tech. Compete	0.03	-0.11	0.22	0.16	0.12	0.04											
8. Internet Usage	0.04	-0.05	0.00	0.00	-0.03	0.02	0.27										
9. Involvement	0.02	-0.01	0.14	0.00	0.11	0.02	0.07	0.03									
10. Price sensitivit	0.09	-0.01	0.12	-0.08	-0.17	0.04	0.03	0.05	0.03								
11. Portal OBS Cluster Usage	0.07	0.01	-0.02	-0.02	-0.05	0.02	-0.01	0.05	-0.01	0.06							
12. Found Price Info	-0.01	-0.07	0.02	0.09	0.07	0.01	0.15	0.07	0.03	0.06	0.03						
13. Found Vehicle Info	0.02	-0.02	0.07	0.10	0.06	0.00	0.18	0.09	0.02	0.01	0.09	0.49					
14. Product OBS Cluster Usage	-0.03	-0.03	0.04	0.08	0.06	-0.01	0.13	0.07	0.02	0.00	0.13	0.12	0.27				
15. Price OBS Cluster Usage	-0.04	-0.10	0.06	0.10	0.08	0.00	0.17	0.08	0.01	0.06	0.05	0.26	0.20	0.18			
16. Purchase Price	0.01	-0.13	-0.14	0.17	0.53	-0.06	0.03	-0.01	0.22	-0.16	-0.04	-0.02	-0.01	0.01	0.02		
17. Vehicle Choice Impact	-0.07	0.00	-0.16	-0.07	0.01	-0.04	-0.17	-0.11	-0.05	-0.04	-0.05	-0.21	-0.26	-0.17	-0.14	0.08	
18. Satisfaction	0.06	-0.01	0.17	0.04	0.02	0.04	0.23	0.14	0.06	0.07	-0.02	0.32	0.26	0.10	0.21	-0.01	-0.41