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Recommended for you: The effect of word of mouth on sales concentration

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ABSTRACT

I examine the role of word of mouth in consumer's product discovery process and its implications for the firm. A monopolist supplies an assortment of horizontally differentiated products and consumers search for a product that matches their taste by sampling products from the assortment or by seeking product recommendations from other consumers. I analyze the underlying consumer interactions that lead to the emergence of word of mouth, examine the optimal pricing and assortment strategy of the firm, and explain the impact of word of mouth on the concentration of sales within the assortment. The model provides a rationale for the long tail phenomenon, explains recent empirical findings in online retail, and is well suited for product categories such as music, film, books, and video game entertainment.

1. Introduction

Word of mouth (WOM) is fundamental to the product discovery process of consumers. In product categories such as music, film, books, or video games, consumers often identify products that match their taste through the recommendations of others. And with the expansion of electronic commerce, consumers are increasingly accessing these recommendations online. Retailers have embraced the transition by hosting consumer WOM on their websites, inviting consumer feedback about products and displaying it on their product pages. Moreover, retailers are exploiting such feedback to generate personalized product recommendations for their customers. The online retail environment has therefore become an important venue for consumers to obtain product recommendations.

Consider how Amazon exploits product recommendations to foster product discovery. A new customer visiting Amazon.com is presented with bestselling products on the storefront and invited to sign in to "see personalized recommendations." Once the customer has created an account and signed in, the storefront is updated to list product recommendations prominently under headings such as "recommendations for you," "related to items you've viewed," "inspired by your shopping trends," "customers who bought items in your recent history also bought," and so on. Similarly, visiting a product page will list related product recommendations under "what other items do customers buy after viewing this item?" and "customers who bought this item also bought." These product recommendations are generated by an automated recommender system, which exploits Amazon's large stock of consumer feedback to identify potential matches between customers and products. Customers who may have otherwise resorted to offline WOM, seeking product recommendations from others within their social circles, can now readily access an almost endless supply of them through Amazon's algorithms.

This paper presents a model of consumer search to explain the impact of product recommendations on consumer product discovery and the concentration of sales. The model explains the firm's incentives to increase the efficiency of WOM: to lower the cost for consumers to access product recommendations and to improve the matching between consumers and the products they are recommended. The model also explains the consequences of such improvements for consumers and for the concentration of sales within the firm's assortment. Both are intrinsically linked. When consumers with more prevalent preferences are the main beneficiaries of the efficiency improvements, the concentration of sales increases generating a *superstar* effect. This increases the performance of bestselling products. When consumers with less prevalent preferences are the main beneficiaries, as empirical evidence suggests is the case with the recent expansion of electronic commerce, the concentration of sales is reduced generating a *long tail*

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effect. As a result, products representing a small share of total sales (located in the tail of the sales distribution) perform better in the online channel, as first noted by Anderson (2004). The model reconciles lower sales concentration in online retail with the firm's logic for profit maximization, and informs the design of marketing strategies to exploit consumer WOM.

The intuition for the long tail result can be outlined with an example. A large share of the consumer population has mainstream preferences, and a smaller share has niche preferences. Other factors equal, offline WOM tends to benefit mainstream consumers the most, because product recommendations more often originate from consumers with mainstream preferences. This drives mainstream consumers to participate more in the market, which increases the sales of products preferred by mainstream consumers in the offline environment. What happens when the WOM process moves online and improves its efficiency? This levels the playing field across consumers, benefiting those with niche preferences the most. As a result, niche consumers participate more and this increases the sales of their preferred products in the online environment, reducing the concentration of sales and generating a long tail effect.

The example oversimplifies the problem, of course. Consumer search strategies and product prices are jointly determined by the interactions that arise in the marketplace. On the one hand, niche consumers are not dependent on WOM to discover products. They can resort to searching the assortment to discover products that match their taste. On the other hand, the firm will account for the fact that mainstream consumers benefit more from WOM when pricing products, and higher prices can overturn their advantage. The modeling exercise presented below formalizes these aspects of the problem, endogenizing consumer search strategies and product prices, and shows that the long tail effect continues to hold.

1.1. Literature

To the best of my knowledge, no previous theoretical work has explored the links between WOM and sales concentration. Recent literature contributions have explored how changes in consumer search trigger supply-side shifts that affect the concentration of sales. Bar-Isaac, Caruana, and Cuñat (2012) model how reductions in consumer search costs affect product design choices on the supply side of the market, which can lead to lower sales concentration by increasing the market shares of firms with rare designs. Yang (2013) analyzes how consumer search costs and targetability affects product variety, and shows that improvements in search can lower the concentration of sales by ensuring that less popular product varieties are produced by firms. These contributions provide important insights on how consumer search affects the variety of products supplied in the market, and therefore the concentration of sales.

Recent empirical evidence suggests that factors beyond the variety of products supplied are contributing to lower sales concentration online. Brynjolfsson, Hu, and Simester (2011) examine sales concentration within the assortment of a multi-channel clothing retailer and find that, even when supply-side factors such as product availability and visibility are held constant, the Internet channel exhibits significantly less concentration than the catalog channel. Elberse and Oberholzer-Gee (2008) report similar findings comparing the offline and online sales of a large sample of DVD and VHS video titles. This paper shows that improvements in the efficiency of WOM, for instance driven by recommender systems, can explain these findings.

The empirical literature has also shown that facilitating WOM and personalized product recommendations has a positive impact on sales, consistent with the findings derived below. Chevalier and Mayzlin (2006) analyze the impact of consumer reviews of books on Amazon and Barnes and Noble's websites, and find that reviews increase the relative sales at the retailer they are posted on. De, Hu, and Rahman (2010) examine online retailer activity logs and show that recommender systems increase sales volume. Moreover, and consistent with the model's predictions when niche consumers benefit the most, recommender systems have been shown to lower the concentration of sales. In their study of a multi-channel retailer cited above, Brynjolfsson et al. (2011) analyze the retailer's website logs and find that the recommender system is the major contributor to the concentration shift observed in online sales. Oestreicher-Singer and Sundararajan (2010) find that sales concentration is lower among book categories on Amazon.com where the recommender system is expected to be more accurate. Ehrmann and Schmale (2008) report similar findings on Amazon.de. Fleder and Hosanagar (2007) use simulations to evaluate the impact of different recommender systems on sales concentration and sales volume.

Recent contributions also find that niche consumers benefit the most from online WOM. Zhu and Zhang (2010) show that online consumer reviews of video games have a stronger impact on niche products. Tan and Netessine (2011) examine the supply of new titles on Netflix and conclude that recommender systems play an important role in guiding niche consumers to discover new releases. Sun (2011) shows that product ratings are more informative for niche consumers when presented together with the variance of ratings, as is frequently the case in online retail. Choi and Bell (2011) argue that e-commerce attracts preference minorities who are not well served by brick and mortar stores due to the constraints of physical distribution.

1.2. A search framework for WOM

I build on the modeling foundation for consumer search with differentiated products developed by Wolinsky (1986) and extended by Anderson and Renault (1999). Consumers arrive to the market uninformed about products. Each consumer can become informed by sequentially drawing products from the assortment, incurring a search cost on each product draw and observing the price and the utility derived from the product. Consumers form a correct expectation of the value of search and decide whether participate or not in the market. I focus on the monopoly case where all products are supplied by a single firm, so consumers search across the firm's assortment.[1]

The modeling foundation assumes that consumers observe product price and product utility simultaneously on each draw. This keeps the analysis simple by ensuring that consumers do not infer product utility based on product price, or vice versa. For example, if consumers could observe product prices before searching – given that product prices are more salient than product utility in many retail contexts – they could use this information to infer product utility without engaging in search (if the firm sets a different price for each product type in equilibrium). The assumption rules out the possibility that the firm uses prices as a signaling device to reduce consumer search costs, which is reasonable for categories where products are horizontally differentiated such as music, films, books, or video games. In these categories, consumer preferences are highly idiosyncratic and prices tend to be a weak predictor of the utility of products.[2]

[1] Search costs can be interpreted as the costs of acquiring information in the market. A consumer with zero search cost (consumer $s_i = 0$ in the model) incurs no positive cost to observe the price and the utility derived from all products. Note that if all consumers had zero search costs, the outcome is equivalent to the case where consumers are perfectly informed about the assortment. In this case all products are priced at u, all consumers purchase, and no word of mouth arises because consumers do not benefit from product recommendations.

[2] When products are vertically differentiated, standard models predict that price and quality are positively correlated. For example, if smartphones can be ranked according to technical specifications and consumers agree that these specifications are the relevant dimension of differentiation in this product category, then consumers can correctly infer that a high-price smartphone will yield higher utility than a low-price smartphone. In models of horizontal differentiation, in contrast, prices are not informative of the utility provided by products. High-price products can yield lower utility than low-price products to some consumers. For example, it can be argued that the retail price of a book is a poor predictor of the utility it will provide to a reader. The analysis is therefore better suited to product categories where the horizontal differentiation dimension prevails.

I consider two product types and two consumer types in the model, which simplifies the analysis though the results extend to a larger number of types. I enrich consumer search by letting consumers choose among two alternative search strategies: they can search the assortment by sampling products directly (as in standard search models) or they can search with WOM by seeking product recommendations. The odds when drawing from the assortment will depend on the assortment's product composition, and the odds when drawing recommendations will depend on the composition of consumers who provide them. Assortment search takes place first, so consumers who search the assortment become the providers of recommendations in the market. The richness of the setup originates from the interdependencies that arise with WOM: if more consumers of a given type search the assortment, consumers of that type will benefit more from drawing recommendations. This implies that the utility that consumers derive from WOM is endogenously determined in equilibrium, and will depend on the search strategy choices across the whole consumer population.

The motivation for this approach is twofold. First, it addresses the chicken-and-egg problem of how consumers become informed about products in order to provide recommendations to others. Clearly, some consumers have to explore the assortment first for others to benefit from informed recommendations, so incorporating assortment search into the problem explicitly accounts for this process. And second, it allows the model to explain the emergence of WOM and the composition of consumers who participate in it. Given that consumers can search the assortment or stay out of the market instead of searching with WOM, they will only do so if it pays off.

The efficiency of WOM in the model hinges on two factors: the cost for consumers to obtain product recommendations and the degree of preference matching in the process, which increases the likelihood that consumers are recommended one of their preferred products. This allows the model to encompass recommender systems in the context of online retail as well as traditional WOM exchanges in the offline context. In the online environment, the cost of recommendations is low because recommender systems readily supply recommendations on demand. In the offline environment, the cost of recommendations is higher because consumers need to engage in social interactions to obtain them. The degree of preference matching is high in the online context because recommender systems "match" consumers based on their product preferences, increasing the likelihood of successful recommendations.[3] In the offline context there is no matching mechanism intermediating the exchange, so preference matching tends to be lower. Nonetheless, consumers can seek to interact with those who provided successful recommendations in the past, so the degree of matching in the offline context will increase with consumer's awareness of the product preferences of others (i.e., with the observability of consumption patterns or opportunities for joint consumption).

I need to make assumptions about the provision of product recommendations to model the WOM exchange. I proceed by assuming that consumers only provide recommendations in the market when this benefits others. The setup can be understood as a *pull-based* WOM process, where consumers only "speak" when others who share their product preferences "listen." So when consumers of both types search with WOM, consumers of both types who previously searched the assortment provide recommendations. And when only one consumer type searches with WOM, only consumers of that same type provide recommendations. In the online context, the setup can be reconciled with the fact that recommender systems exhibit high accuracy when addressing a homogeneous audience (a single consumer type).[4] In the offline context, the setup implies that consumers are not willing to engage in the WOM exchange when no-one shares their product preferences. I discuss the potential implications of a *push-based* WOM process where consumers speak regardless of who listens in Section 4.

The next section formalizes the building blocks of the model, and Table 1 summarizes the notation. Consumer search strategies are characterized as a function of product prices in Section 3, which explains the drivers of WOM in the model. Section 4 solves equilibrium prices and explains the implications of word of mouth for the firm. I analyze the impact of word of mouth on the concentration of sales within the firm's assortment in Section 5, and examine the implications for assortment composition in Section 6. Managerial implications are summarized in Section 7, and Section 8 concludes.

2. The model

Consider a market where a monopolist supplies a product assortment consisting of a continuum of products of measure one. There is a unit mass of consumers who differ in their product preferences and in their search costs. The simplest instance of the model that yields the results is that where there are two types of products over which consumers exhibit a strict preference ranking. To this end, I partition the assortment into two product types and consider two consumer types. A share a of products in the assortment is of type 1, and the remaining share $1 - a$ is of type 2. Similarly, there is a share m of consumers of type 1 and there is a share $1 - m$ of consumers of type 2. All consumers derive utility u from products of their same type and zero utility from the remaining.

The problem is of interest when the shares of both types differ across consumers and products. Let $m \in \left(\frac{1}{2}, 1\right)$ so that consumers of type 1 are more prevalent in the population, so I will refer to consumers of type 1 as *mainstream* consumers and to consumers of type 2 as *niche* consumers. Similarly, let $a \in \left(\frac{1}{2}, 1\right)$ so that products of type 1 are more prevalent (or prominent) in the assortment. I will refer to products of type 1 that appeal to mainstream consumers as mainstream products, and to products of type 2 as niche products.

Consumers face a search problem. They do not observe the utility and the price of individual products when arriving to the market, so all products appear ex-ante identical. Consumers need to search in order to identify which products are of their preferred type and observe their prices. Consumers exhibit unit demand, and may participate in the market to search for and purchase one of their preferred products or stay out. A product *match* is achieved when a preferred product is identified. Consumers can locate a match either by searching the assortment or by searching with WOM.

The timing of the game is as follows. In the first stage, the firm sets prices p_1 and p_2 for mainstream and niche products, respectively. In the second stage, consumers may search the assortment by sequentially drawing products. Consumers draw products randomly from the assortment to sample them, and learn the utility they provide and observe their price. If a draw yields a match (the product is of the same type as the consumer and yields utility u), the consumer purchases the product

[3] Collaborative filtering algorithms play an important role in recommender systems. The simplest instance of a collaborative filter exploits a database containing a set C of consumers, a set N of products, and the ratings that consumers have provided for products. If consumer c_i has not rated product n_k, an expected value for that rating can be calculated by $E[Rating\,(c_i, n_k)] = \sum_{j \in C} Similarity\,(c_i, c_j) * Rating(c_j, n_k)$, where the similarity function measures the taste proximity of any two consumers based on the correlation of their past product ratings. The algorithm will recommend to consumer c_i the unrated product which obtains a higher expected rating. Thus the algorithm can be interpreted to "draw" from the customer base and "match" consumers with similar preferences in the process, increasing the likelihood of a successful recommendation. See Adomavicius and Tuzhilin (2005) for a taxonomy of recommender systems and an overview of the related computer science literature. For a brief discussion on the economics of recommender systems, see Resnick and Varian (1997).

[4] The recommender's task is simplified when the target audience becomes more homogeneous because this reduces the variance in the success rate of product recommendations across consumers. Nonetheless, market configurations where only one consumer type searches with word of mouth are more relevant to the offline context. The analysis reveals that both consumer types have strong incentives to seek product recommendations when preference matching τ is high and recommendation cost w is low, as is the case in the presence of a recommender system.

Table 1
Key notation used in the paper.

t	Consumer and product types, where 1 = mainstream and 2 = niche
m	Share of mainstream consumers in the population
a	Share of mainstream products in the assortment
p	Product prices
u	Consumer utility derived from a preferred product
s	Cost of sampling a product from the assortment
w	Cost of drawing a product recommendation
τ	Degree of preference matching with recommendations
μ	Expected utility of a new draw
β	Match probability when drawing from the assortment
α	Match probability when drawing a product recommendation
U	Total expected utility of search
D	Demand
π	Firm profits
MS	Product market shares

and exits the market. Otherwise, the consumer continues to draw products until a match is located.

In the third stage, consumers may search with WOM by sequentially drawing product recommendations. These recommendations are provided by consumers who searched the assortment in the second stage, who recommend the product they matched with to others. Alternatively, recommendations can be interpreted to be provided by a recommender system, which intermediates between consumers drawing recommendations and consumers who searched the assortment (who provide input to the algorithm). Each recommendation enables the consumer to learn the utility derived from the recommended product and observe its price. If this results in a match, the consumer purchases the product and exits the market. Otherwise the consumer continues to draw recommendations until a match is located.

I model the supply and demand of product recommendations with a pull-based process (see the preceding section for a discussion of the setup). When mainstream and niche consumers search with WOM, consumers of both types who previously searched the assortment provide recommendations. Parameter τ captures the degree of preference matching in the WOM process. On each recommendation draw, with probability $\tau \in (0, 1)$ the consumer draws a recommendation from another consumer of her own type, and with probability $1 - \tau$ draws a recommendation randomly from the mass of consumers supplying them. The probability of a product match on each draw is therefore increasing in τ. When only mainstream consumers or only niche consumers search with WOM, only consumers of that same type provide recommendations. In these cases, recommendations will always yield a match.

Search is costly for consumers. Each consumer incurs a sampling cost s_i on each product draw when searching the assortment, and incurs a recommendation cost w on each recommendation draw when searching with WOM. Sampling costs are uniformly distributed across the population independently of product preferences, so that the cost of consumer i is given by $s_i \sim U[0, \bar{s}]$. Letting consumers differ in their search costs ensures that some will prefer to search the assortment in equilibrium while others will prefer to search with WOM. I assume that $\bar{s} \geq u$ so that some consumers are unwilling to search the assortment, which simplifies the analysis by avoiding corner solutions in the pricing game. I also assume that consumers have the information required to form a correct expectation of the value of both search strategies: they observe mainstream population m, assortment composition a, and product prices p_1 and p_2.

3. Consumer search strategies

I proceed by backwards induction and solve for consumer search strategy choices in the second and third stages. The model provides a rich search framework, and it is useful to review its properties before solving first-stage equilibrium prices in the next section. First I characterize the utility of search with WOM in the third stage, then I turn to assortment search in the second stage, and then pin down consumer choices by comparing the expected utility of both.

3.1. WOM search

Consider the problem of an unmatched consumer of type $t \in \{1, 2\}$ in the third stage. Searching with WOM implies sequentially drawing product recommendations until a match is located. Denote the probability of locating a product match on each recommendation draw for consumers of type t by α_t. A recommendation will only yield a match if drawn from another consumer of the same type. Thus α_t depends on preference matching τ and the share of consumers of each type that provide recommendations, to be denoted by r_t. There is always a positive mass of consumers providing recommendations, as will be shown below to be the case, so α_t remains constant throughout the search. Each recommendation draw is a Bernoulli trial with the same success probability for all consumers of type t given by

$$\alpha_t = (1-\tau)r_t + \tau. \quad (1)$$

The expected utility of drawing a new recommendation for an unmatched consumer of type t given α_t when her preferred products are priced at p_t, to be denoted by μ_t^w, is given by

$$\mu_t^w = \alpha_t(u-p_t)-w, \quad (2)$$

as the consumer only purchases if a match is located but incurs recommendation cost w on every draw. Note that μ_t^w will differ across both consumer types due to match probability α_t and prices p_t.

Consumers of type t will prefer to search with WOM rather than staying out of the market if $\mu_t^w \geq 0$. Consumers searching with WOM sequentially draw recommendations until they obtain a match, which on average requires $1/\alpha_t$ draws for a consumer of type t. The search process finalizes once a match is located, searching for a second match cannot provide additional utility given the assumption that consumers exhibit unit demand.

3.2. Assortment search

I next turn to the second stage of the game and characterize direct search through the assortment. Searching the assortment implies sequentially drawing and sampling products, and a match is obtained when drawing a product of the consumer's own type. Denote the match probability on each assortment draw for consumers of type t by β_t, where $\beta_1 = a$ and $\beta_2 = 1 - a$. Given that β_t remains constant throughout the search, each assortment draw is a Bernoulli trial with success probability β_t for all consumers of type t.

The expected utility of a new product draw for an unmatched consumer of type t with sampling cost s_i when her preferred products are priced at p_t, to be denoted by $\mu_{t,i}^a$, will be given by

$$\mu_{t,i}^a = \beta_t(u-p_t)-s_i, \quad (3)$$

given that the consumer only purchases if a match is located but incurs sampling cost s_i on each draw. Note that $\mu_{t,i}^a$ will vary across types depending on assortment composition a (through β_t) and prices p_t, and will also vary within types depending on consumer sampling cost s_i.

The indifferent participant of type t, denoted by $s_t^{\hat{a}}$, is strictly indifferent between searching the assortment and not participating in the market. This consumer can be identified by substituting s_i for $s_t^{\hat{a}}$ in Eq. (3) and solving for $\mu_{t,i}^a = 0$,

$$s_t^{\hat{a}} = \beta_t(u-p_t). \quad (4)$$

Consumers of type t with sampling cost $s_i \leq s_t^{\hat{a}}$ prefer to search the assortment rather than staying out of the market. Consumers searching the assortment sequentially draw products until a match is located, which on average requires $1/\beta_t$ draws for a consumer of type t. The search process finalizes once a match is located given that consumers exhibit unit demand.

3.3. Search strategy choices

I next analyze the search strategy choices of consumers in the second stage. Note that consumers of type t with low sampling costs ($s_i \leq s_t^{\hat{a}}$) derive positive utility from both search strategies when $\mu_t^w \geq 0$. These consumers will choose which search strategy to pursue by comparing the expected utility of both. Consumers will perform this comparison by accounting for the fact that the expected number of draws required for a match differs between both strategies, as given by $1/\beta_t$ and $1/\alpha_t$. Let $U_{t,i}^a = \mu_{t,i}^a/\beta_t$ and $U_t^w = \mu_t^w/\alpha_t$ denote the (total) expected utility of searching the assortment and searching with WOM, respectively, for a consumer of type t with search cost s_i. Note that the expected utility of both search strategies is unaffected by past unsuccessful draws, so a consumer who prefers to search the assortment in the second stage will never abort the search in order to search with WOM in the third stage.[5]

The indifferent searcher of type t, denoted by $s_t^{\hat{w}}$, obtains the same expected utility from both search strategies. The indifferent searcher is identified by equating $U_{t,i}^a = U_t^w$,

$$u - p_t - \frac{s_i}{\beta_t} = u - p_t - \frac{w}{\alpha_t}, \quad (5)$$

and substituting s_i for $s_t^{\hat{w}}$ and rearranging,

$$s_t^{\hat{w}} = \frac{w\beta_t}{\alpha_t\left(s_t^{\hat{w}}\right)}. \quad (6)$$

The solution is given by an implicit equation because α_t depends on $s_1^{\hat{w}}$ and $s_2^{\hat{w}}$ when $r_t < 1$ (when both consumer types search with WOM). I solve the system below.

I can now characterize the search strategy choices of consumers. When $\mu_t^w \geq 0$, consumers of type t with sampling cost $s_i \leq s_t^{\hat{w}}$ search the assortment in the second stage and those with sampling cost $s_i > s_t^{\hat{w}}$ search with WOM in the third stage. When $\mu_t^w < 0$, consumers of type t with sampling cost $s_i \leq s_t^{\hat{a}}$ search the assortment in the second stage and the remaining stay out of the market.

3.4. Market configurations

There are four possible combinations of search strategy choices given the two consumer types. When $\mu_1^w \geq 0$ and $\mu_2^w \geq 0$ both types search with WOM (market configuration WW), when $\mu_1^w \geq 0$ and $\mu_2^w < 0$ only mainstream consumers search with WOM (configuration WA), when $\mu_1^w < 0$ and $\mu_2^w \geq 0$ only niche consumers search with WOM (configuration AW), and when $\mu_1^w < 0$ and $\mu_2^w < 0$ neither type searches with WOM (configuration AA).

3.5. Closed-form solution

I next pin down equilibrium search strategies as a function of prices. Let $c \in \{ww, wa, aw, aa\}$ identify the four market configurations. For consumer types that search with WOM in market configuration c, denote the indifferent searcher by s_t^c. Consider first configuration WW where both types search with WOM. In this configuration, consumers of both types provide recommendations. The shares of consumers of each type providing recommendations can be written as a function of the indifferent searchers,

$$r_1 = \frac{(s_1^{ww}/\bar{s})m}{(s_1^{ww}/\bar{s})m + (s_2^{ww}/\bar{s})(1-m)}$$
$$r_2 = \frac{(s_2^{ww}/\bar{s})(1-m)}{(s_1^{ww}/\bar{s})m + (s_2^{ww}/\bar{s})(1-m)}.$$

Plugging the above expressions for r_1 and r_2 into α_t in Eq. (1) for each type, and then plugging α_1 and α_2 into Eq. (6) for each type and substituting $s_1^{\hat{w}}$ for s_1^{ww} and $s_2^{\hat{w}}$ for s_2^{ww} provides a system of two equations. The system has a unique solution satisfying $s_1^{ww} > 0$ and $s_2^{ww} > 0$, which is given by

$$s_1^{ww} = \frac{w(2am-(1-a-m)\tau + M)}{2m(1+\tau)}$$
$$s_2^{ww} = \frac{w(2+\tau-(a+m)\tau-2(1-a)m-2a+M)}{2(1-m)(1+\tau)}$$

where

$$M = \sqrt{4(1-a)(1-m)am + (1-a-m)^2\tau^2}. \quad (7)$$

Denote the equilibrium match probability of a recommendation draw for consumers of type t in market configuration c by α_t^c. The above solution implies that

$$\alpha_1^{ww} = \frac{2am-(a+m-1)\tau-M}{2(a+m-1)}$$
$$\alpha_2^{ww} = \frac{m(2-2a+\tau)-(1-a)(2+\tau)+M}{2(a+m-1)}. \quad (8)$$

Consider next market configurations WA and AW, where only one type searches with WOM. Only consumers of the type searching with WOM will provide recommendations, so recommendations always yield a match. Therefore,

$$s_1^{wa} = w\beta_1 \quad (9)$$
$$s_2^{aw} = w\beta_2$$
$$\alpha_1^{wa} = 1$$
$$\alpha_2^{aw} = 1.$$

For types that search only the assortment in configurations WA, AW, and AA, let s_t^c denote the indifferent participant of type t in market configuration c. The solution is given by $s_t^{\hat{a}}$ in Eq. (4),

$$s_1^{aw} = a(u-p_1)$$
$$s_2^{wa} = (1-a)(u-p_2)$$
$$s_1^{aa} = a(u-p_1)$$
$$s_2^{aa} = (1-a)(u-p_2).$$

Lemma 1. *Consumer search strategies as a function of prices $\{p_1, p_2\}$ are characterized by sampling cost cutoffs $\{s_1^c, s_2^c\}$ in market configuration $c \in \{ww, wa, aw, aa\}$: consumers of type t with low sampling cost search the assortment ($s_i \leq s_t^c$) and consumers with high sampling cost ($s_i > s_t^c$) search with WOM (mainstream consumers in configurations WW and WA, niche consumers in configurations WW and AW) or otherwise stay out of the market. This implies that consumers who search with WOM have a lower willingness to pay than those who search the assortment, and mainstream consumers benefit more from WOM than niche consumers.*

[5] The expressions for $U_{t,i}^a$ and U_t^w can also be derived as follows. Because β_t remains constant when drawing from the assortment, $U_{t,i}^a = \beta_t(u-p_t) + (1-\beta_t)U_{t,i}^a - s_i$, which implies that $U_{t,i}^a = u - p_t - (s_i/\beta_t)$. Similarly, given that α_t remains constant when drawing recommendations, $U_t^w = \alpha_t(u-p_t) + (1-\alpha_t)U_t^w - w$, so that $U_t^w = u - p_t - (w/\alpha_t)$. Equating $U_{t,i}^a = U_t^w$ delivers expression (5).

Consumers evaluate the expected utility of both search strategies when deciding whether to participate or not in the market and which search strategy to pursue. The cost of each draw differs between searching the assortment and searching with WOM depending on the consumer's sampling cost s_i and recommendation cost w. The expected number of draws required to locate a match also differs. The odds when drawing from the assortment depend on the assortment's composition, and the odds when drawing recommendations depend on the composition of consumers providing recommendations and the degree of preference matching τ. It is useful to define the value of WOM as a function of τ and w:

Definition. The *value of WOM* for all consumers increases with the degree of preference matching τ and decreases with recommendation cost w.

An increase in the value of WOM reduces the search costs consumers incur to locate a match with recommendations.[6] If the value of WOM is too low, some consumers will prefer to stay out of the market instead of searching with WOM. I next focus on the case where consumers of both types are willing to search with WOM (market configuration WW), which is the case where the interactions between types is of most interest.

The left panel in Fig. 1 plots the expected utility of search strategies. Utilities are plotted for the benchmark case where the assortment share and the price of both product types coincide ($a = 1/2$ and $p_1 = p_2$), which implies that the expected utility of searching the assortment also coincides for both types $U^a_{1,i} = U^a_{2,i}$. Note that consumers with low sampling costs prefer to search the assortment and consumers with high sampling costs prefer to search with WOM. This follows from the fact that consumers with low sampling costs suffer comparatively less from failed assortment draws than consumers with high sampling costs. Thus consumers who choose to search with WOM incur higher search costs than those who search the assortment, and as a result exhibit a lower willingness to pay. The sampling cost cutoffs between both search strategies s^{ww}_1 and s^{ww}_2 also vary across types due to the interdependencies that arise with WOM: the larger the share of consumers of a given type that search the assortment and provide recommendations, the lower the expected number of recommendation draws required by consumers of that type to locate a match.

An important property of the solution is that mainstream consumers benefit more from WOM. This is due to the fact that mainstream consumers enjoy a higher success rate when drawing recommendation than niche consumers ($\alpha^{ww}_1 > \alpha^{ww}_2$) because more mainstream consumers provide recommendations. Simply stated, they benefit from the fact that their preferences are more prevalent in the population. This mainstream advantage increases with mainstream population m and decreases with the value of WOM, because efficiency improvements in the WOM process benefit niche consumers comparatively more. The right panel in Fig. 1 illustrates the effect by plotting search strategy choices as a function of preference matching τ: the higher the value of WOM (higher τ) the closer the sampling cost cutoffs of both types, and thus the lower the advantage of mainstream consumes. Reductions in recommendation cost w have a similar effect.

The preceding analysis characterizes positive WOM, given that consumers providing recommendations inform others about the products they matched with (products they derive utility from). This reflects the observation that consumers tend to discuss the media products they enjoy, rather than the ones they do not. However, consumers could also provide recommendations about products they became informed about that did not yield a match, due to failed draws from the assortment. Both positive and negative WOM would then coexist in the market. In this case, when consumers providing recommendations draw randomly from their search history and all recommendations are informative about products, it can be shown that the match probability with recommendations is equivalent to that of drawing directly from the assortment, $\alpha_t = \beta_t$. WOM then provides more information about products with a lower match probability for the majority of consumers. This hurts mainstream consumers and benefits niche consumers, so the consumer population as a whole is better off with positive WOM only.[7]

4. Equilibrium prices and market configurations

I turn to the firm's pricing problem in the first stage of the game. Before proceeding, it is useful to put additional structure on the problem to rule out market configuration multiplicity for certain price ranges:

Assumption. When prices p_1 and p_2 are such that both market configuration WA and market configuration AW can be sustained, configuration WA prevails in the marketplace.

The assumption ensures that the equilibrium of the pricing game is unique. For certain prices the market can only sustain WOM by a single consumer type and this generates equilibrium multiplicity.[8] Intuitively, WOM is most valuable for consumers when those participating in the exchange exhibit the same preferences, and for some prices it can be supported by either mainstream consumers or niche consumers. The assumption resolves this multiplicity by selecting the equilibrium where mainstream consumers prevail (or equivalently, the welfare-maximizing equilibrium). This can be interpreted as the mainstream majority crowding out the niche minority in the WOM exchange when the participation of both is unsustainable. The assumption reduces the equilibrium region of market configuration AW but does not affect the qualitative results of the analysis.

I next characterize the firm's demand and the price region for each market configuration to arise. Then I analyze the firm's optimal pricing within each configuration. I determine the properties of the equilibrium by comparing the firm's profit frontiers across the four configurations.

4.1. Firm demand

The demand for products of type t depends on the participation of consumers of type t in the market, which in turn depends on their search strategy choices. Let D^c_t denote the demand for products of type t in market configuration c. Note that D^c_t is only well defined for prices such that configuration c holds, that is, prices that ensure that consumer search strategy choices are consistent with configuration c. Demands can be

[6] Recommendations enjoy no salience in the model, because consumers do not place additional value on a match that results from a recommendation. Senecal and Nantel (2004) report a series of experiments that suggest that recommendations have an influential effect on consumers beyond awareness. If salient recommendations increase the utility that consumers derive from a product match, then salience can be interpreted to increase the value of word of mouth in the market.

[7] It is worth stressing that negative word of mouth can generate sales in the context of horizontally differentiated products. Consumers care about how products fit with their idiosyncratic preferences and not about their fit with other consumers (e.g., a mainstream consumer engaging in negative word of mouth about a niche product can yield a match for a niche consumer). In the context of vertically differentiated products, negative word of mouth tends to reduce sales because all consumers agree on the determinants of product utility. The literature suggests that the underprovision of recommendations and their manipulation by interested parties are relevant factors in this context. Avery, Resnick, and Zeckhauser (1999) characterize reward schemes for the optimal provision of recommendations and Dellarocas (2006) analyzes the implications of strategic manipulation of recommendations.

[8] Multiplicity arises for prices where both $\mu^w_1 \geq 0$ and $\mu^w_2 < 0$ (configuration WA) as well as $\mu^w_1 < 0$ and $\mu^w_2 \geq 0$ (configuration AW) can be sustained in equilibrium. The precise range of prices is characterized by $p_1 \in [p^{ww}_1, p^{wa}_1]$ and $p_2 \in [p^{ww}_2, p^{aw}_2]$.

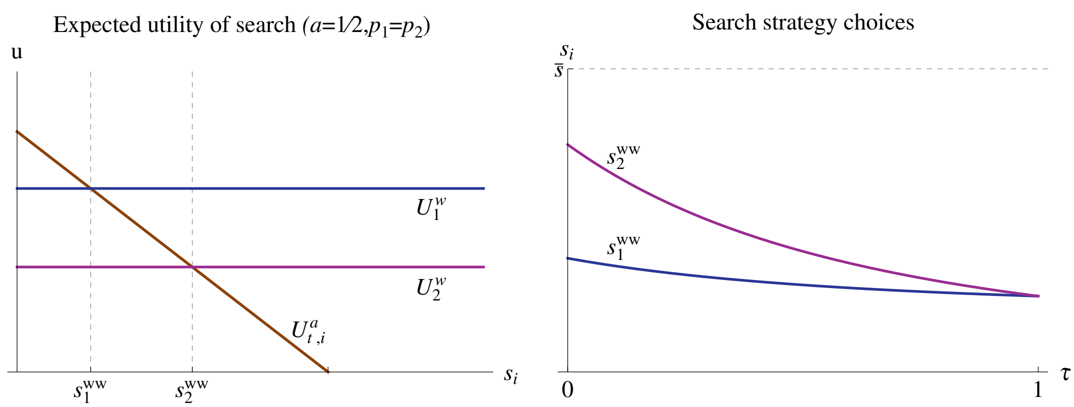

Fig. 1. On the left, expected utility of both search strategies for mainstream and niche consumers as a function of their sampling cost s_i keeping other factors equal. Mainstream consumers stand to benefit the most from word of mouth. On the right, search strategy choices as a function of preference matching τ. Mainstream advantage decreases with the value of word of mouth for consumers.

written based on the characterization of consumer search strategies derived in Lemma 1,

$$\begin{aligned}
D_1^{ww} &= D_1^{wa} = m \\
D_2^{ww} &= D_2^{aw} = 1-m \\
D_1^{aw} &= D_1^{aa} = \frac{(u-p_1)a}{\bar{s}} m \\
D_2^{wa} &= D_2^{aa} = \frac{(u-p_2)(1-a)}{\bar{s}} (1-m).
\end{aligned} \tag{10}$$

I next characterize the price region for each market configuration to hold. Let p_t^c denote the threshold price which ensures consumers of type t searching with WOM in market configuration c are indifferent between participating or not in the market. Plugging α_t^c in Eqs. (8) and (9) into μ_t^w in Eq. (2), and substituting p_t for p_t^c to solve for $\mu_t^w(p_t^c) = 0$ in each case identifies the following threshold prices,

$$\begin{aligned}
p_1^{ww} &= u - \frac{2am-(1-a-m)\tau + M}{2am(1+\tau)} w \\
p_2^{ww} &= u - \frac{2(1-a-m)}{2(1+am-a-m)+\tau(1-a-m)-M} w \\
p_1^{wa} &= u-w \\
p_2^{aw} &= u-w,
\end{aligned} \tag{11}$$

where M is given by Eq. (7).

The left panel in Fig. 2 depicts the price regions of the four market configurations given the threshold prices derived above. By assumption, note that WA prevails in the central region delimited by the four threshold prices. The right panel illustrates the firm's problem by plotting the demand for mainstream products when $p_2 < p_2^{ww}$. There is a high level of demand when mainstream consumers search with WOM, that is, when mainstream products are priced below threshold price p_1^{ww}. When mainstream products are priced above p_1^{ww}, mainstream consumers search the assortment only and this reduces demand because consumers with high sampling costs do not participate. The demand curve therefore encompasses two market configurations, and is composed by D_1^{ww} in the low price range and D_1^{aw} in the high price range (as shown in the left panel, p_1^{ww} is the frontier between configurations WW and AW when $p_2 < p_2^{ww}$).

4.2. Firm pricing

I next analyze the firm's pricing problem by separately considering each of the four market configurations. Denote the firm's profits in market configuration c by π^c, where $\pi^c = D_1^c p_1 + D_2^c p_2$ given demands in Eq. (10). First, inspection of price regions for configurations WW, WA, and AA, depicted in the left panel of Fig. 2, reveals that the firm can set any feasible price for one type without constraining the feasible price range for the other type (i.e., the regions are rectangular). For configuration AW, however, the firm has to choose between setting a high p_2 and setting a low p_1 (i.e., the price region is not rectangular). Inspection of π^{aw} reveals that the firm solves this tradeoff by always setting the highest feasible price p_2.[9]

I proceed to identify the firm's optimal prices within each of the four market configurations. Inspection of π^c across the four configurations reveals that $\partial\pi^c/\partial p_t > 0$ for types t that search with WOM in configuration c. For types that do not search with WOM, solving first-order condition $\partial\pi^c/\partial p_t = 0$ obtains $p_t = u/2$ in all cases. Inspection of second-order conditions confirms that this solution is indeed a maximum in all cases. Let p_t^c (with a slight abuse of notation) denote the optimal price for products of type t in market configuration c. Based on the preceding analysis, optimal prices for types that search with WOM coincide with threshold prices in Eq. (11). For types that do not search with WOM, optimal prices are given by

$$\begin{aligned}
p_2^{wa} &= \begin{cases} u/2 & \text{if } u/2 > p_2^{ww} \\ p_2^{ww} & \text{otherwise} \end{cases} \\
p_1^{aw} &= \begin{cases} u/2 & \text{if } u/2 > p_1^{wa} \\ p_1^{wa} & \text{otherwise} \end{cases} \\
p_1^{aa} &= \begin{cases} u/2 & \text{if } u/2 > p_1^{wa} \\ p_1^{wa} & \text{otherwise} \end{cases} \\
p_2^{aa} &= \begin{cases} u/2 & \text{if } u/2 > p_2^{aw} \\ p_2^{aw} & \text{otherwise} \end{cases}
\end{aligned} \tag{12}$$

4.3. Equilibrium market configurations

Given optimal prices within each market configuration, the firm will compare profits across the four configurations when choosing which prices to set. Substituting optimal prices given in Eqs. (11) and (12) into π^c obtains the firm's profit frontier for each market configuration, to be denoted by π^{c^*}. The firm's problem is then equivalent to choosing among the four possible market configurations.

[9] Inspection of π^{aw} reveals that it attains a higher value on the segment given by $p_2 = p_2^{aw}$ and $p_1 \in [p_1^{wa}, u]$ than in the remaining of the region. Thus the firm's price solution in region AW must be located in the uppermost frontier of the region. This implies that the lower bound on p_1^{aw} in Eq. (12) is given by p_1^{wa} (and not p_1^{ww}), given that $p_1 < p_1^{wa}$ would trigger a shift to market configuration WA.

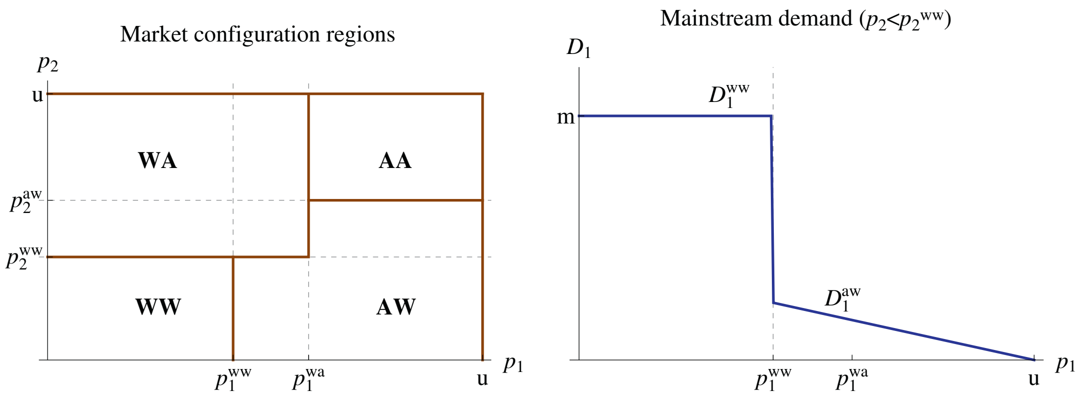

Fig. 2. On the left, price regions of the four market configurations. On the right, demand for mainstream products when $p_2 < p_2^{ww}$, which encompasses configurations WW and AW.

I characterize the firm's solution as a function of WOM cost w. First, consider the ranking of the four profit frontier curves in the corner cases $w = 0$ and $w = u$. When $w = 0$, prices in Eq. (12) bind and $\pi^{ww^*} > \pi^{wa^*} > \pi^{aw^*} > \pi^{aa^*}$. When $w = u$, prices in Eq. (12) do not bind, and $\pi^{ww^*} < \pi^{wa^*} \lessgtr \pi^{aw^*} < \pi^{aa^*}$ (where the ordering of π^{wa^*} and π^{aw^*} varies depending on the remaining parameters). Next, consider the intersections between the profit frontier curves in the range $w \in (0, u)$. Inspection reveals that each pair of profit curves intersects at most once in this range. Denote the intersection between profit frontier curves π^{c^*} and $\pi^{c'^*}$ by $\hat{w}^c_{c'}$. It can be shown that $0 < \hat{w}^{ww}_{wa} < \hat{w}^{wa}_{aw} < \hat{w}^{aw}_{aa} < u$, except when $m \to 1/2$ and $a \to 1$ in which case $\hat{w}^{wa}_{aw} < \hat{w}^{ww}_{aw}$ as well as $0 < \hat{w}^{ww}_{aw} < \hat{w}^{aw}_{aa} < u$ hold.

Consider the impact of a change in preference matching parameter τ. Inspection reveals that $\partial \pi^{ww^*}/\partial \tau > 0$, and the remaining profit curves are unaffected because τ only impacts α_t when both types search with WOM. Thus $\partial \hat{w}^{ww}_{wa}/\partial \tau > 0$ and $\partial \hat{w}^{ww}_{aw}/\partial \tau > 0$, so an increase in τ expands firm profits under market configuration WW and extends the equilibrium range (over w) for such configuration to hold. The above characterization of the firm's frontier profit curves provides the following result.

Proposition 1. *Equilibrium market configurations as a function of w are characterized by the (w-ordered) sequence {WW, WA, AW, AA}, except when $m \to 1/2$ and $a \to 1$ in which case {WW, AW, AA}. The firm sets prices p_1^c and p_2^c in Eq. (11) and Eq. (12) for each configuration c, and firm profits are decreasing in w (across configurations WW, WA, and AW) and increasing in τ (in configuration WW). Therefore, the higher the value of WOM for consumers, the larger the volume of sales and the higher the firm's profits.*

WOM has two main effects on the firm's pricing problem. First, it intensifies the tradeoff between price and quantity: low prices ensure WOM arises and this expands demand, but high prices preclude WOM and thereby contract demand. To understand the effect, recall that consumers who search with WOM are those with high sampling costs and low willingness to pay. When product prices are high, those consumers prefer to stay out of the market and do not purchase. Thus the firm's demand curve for each product type has two components, one corresponding to the low price range where WOM arises (high demand) and another corresponding to the high price range where it does not (low demand). Mainstream demand is plotted in the right panel in Fig. 2, and niche demand exhibits equivalent properties.

Second, the firm needs to discount prices to attract more consumer types to WOM. When more than one consumer type searches with WOM, the exchange of recommendations across types implies that consumers incur unsuccessful recommendation draws ($\alpha_t < 1$). Thus the firm has to further discount prices for both types to search with WOM (configuration WW) compared to the prices that can be sustained for one type alone to search with WOM (configurations WA and AW).

The firm's solution is plotted in Fig. 3. The left panel plots equilibrium profits and the right panel plots equilibrium prices for both product types (mainstream prices are solid, niche prices are dashed), both as a function of recommendation cost w. When w is very high, so that the value of WOM for consumers is low, the firm sets high prices and WOM does not arise in the market (configuration AA). When w is very low, so that the value of WOM is high, the firm prices to ensure that both types search with WOM (configuration WW). For interim values of w, however, the firm sets prices to foster WOM for one type and preclude it for the other type (configurations WA and AW). By doing so, the firm benefits from some degree of WOM while avoiding the exchange of recommendations across types ($\alpha_t = 1$).[10]

The firm's optimal pricing strategy is to sustain high prices while ensuring that WOM arises, discounting prices if necessary. When the value of WOM is low, this implies that the firm discounts prices for types that search with recommendations, and when the value of WOM is high the firm charges a premium. When both types search with WOM (configuration WW) the firm sets higher prices for mainstream products than for niche products. The population advantage enjoyed by mainstream consumers implies that they incur lower search costs than niche consumers, so the firm can extract more surplus from them while still ensuring their participation.

The firm has strong incentives to increase the value of WOM for consumers. That is, reducing consumer search costs allows the firm to appropriate a larger share of consumer surplus, and increasing the efficiency of WOM serves this purpose. As shown in the left panel of Fig. 3, firm profits are increasing in the value of WOM (profits are decreasing in w across configurations WW, WA, and AW, and increasing in τ in configuration WW). This provides a rationale for online retailers to facilitate the exchange of product recommendations on their websites and implement recommender systems that generate personalized recommendations for their customers.

I have analyzed the base scenario where the firm quotes separate prices for mainstream and niche products. If the firm commits to a single price scheme for all products, the optimal price is a population-weighted average of the prices characterized above.

[10] The firm prefers mainstream word of mouth when w is lower (configuration WA) and niche word of mouth when w is higher (configuration AW). A higher w implies that the firm has to discount prices more aggressively to foster word of mouth. Also note that the demand expansion generated by mainstream word of mouth ($D_1^{wa} - D_1^{aa}$) differs from that generated by niche word of mouth ($D_2^{aw} - D_2^{aa}$): there is a larger mass of mainstream consumers ($m > 1/2$), but mainstream consumers tend to participate more than niche consumers when searching only the assortment because there is a larger share of mainstream products ($a > 1/2$). These factors imply that configuration WA is generally more profitable than AW for lower values of w, and vice versa. The equilibrium range over w where market configuration WA holds increases in m and decreases in a, and it can be shown that AW is profit-dominated (by WA and AA) in the corner case $a = 1/2$, and WA is profit-dominated (by AW) in the parameter range where $m \to 1/2$ and $a \to 1$.

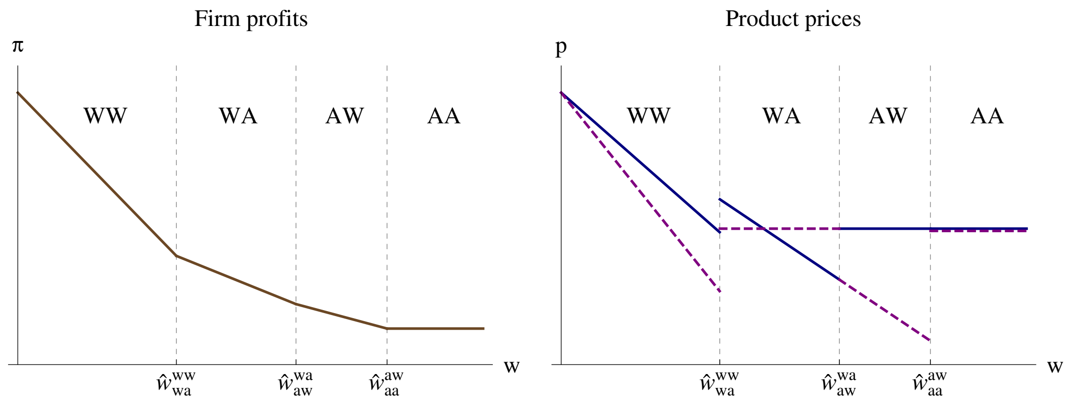

Fig. 3. Firm profits on the left and product prices on the right (mainstream prices are solid and niche prices are dashed) as a function of recommendation cost w. Firm profits are increasing in the value of word of mouth for consumers.

If the firm can price-discriminate consumers based on their search strategies, it can be shown that higher prices are charged to those searching the assortment than to those searching with WOM. The effect analyzed by Kuksov and Xie (2010) of providing lower prices or unexpected frills to early customers in order to profit from later customers is not present, as the utility enjoyed by consumers searching the assortment does not affect the expected utility of consumers searching with WOM.

The firm's solution is derived in the context of a pull-based WOM process, where the provision of recommendations is driven by those seeking them. In a push-based process, the provision of recommendations is driven by those possessing information, so that consumers searching the assortment provide recommendations independently of who seeks them. This affects configurations WA and AW, where the exchange of recommendations across types does not arise in the above analysis but would do so in the context of a push-based process. Unfortunately, a closed-form solution for these push-based cases cannot be derived due to the complexity of the pricing problem. However, inspection of the problem reveals that these configurations become less profitable for the firm, because precluding consumers of one type from searching with WOM no longer reduces search costs for the other type. A push-based process therefore reduces firm profits in configurations WA and AW, reducing the equilibrium range over w where those configurations hold and expanding that of configurations WW and AA, and is less desirable for the firm than a pull-based process.

5. The effect of WOM on sales concentration

I next examine the concentration of sales within the assortment. The exercise is of interest to understand how improvements in the value of WOM, such as those driven by online retail, affect the relative sales of mainstream and niche products. I proceed by characterizing equilibrium market shares of mainstream and niche products in each market configuration and then use the Herfindahl index to rank the four configurations according to sales concentration.

Denote the equilibrium market share of products of type t in market configuration c by MS_t^c. The Herfindahl index is defined as

$$H^c = (MS_1^c)^2 + (MS_2^c)^2.$$

When the difference between mainstream and niche market shares is large, $MS_1^c \gg MS_2^c$, the value of the index is high (high sales concentration) because most sales occur within one product type. When the difference is small, $MS_1^c \approx MS_2^c$, the value of the index is low (low sales concentration) because sales are evenly spread among both. Thus, if mainstream products always outsell niche products so that sales ranks are preserved, an increase in the market share of mainstream products increases index H and a decrease in their market share reduces index H.[11]

5.1. Sales concentration

Market shares are derived by dividing the sales volume generated by products of each type over total sales volume across the assortment, $MS_t^c = D_t^c/(D_t^c + D_{-t}^c)$, where demands are given in Eq. (10). The market shares of mainstream products can be written as a function of equilibrium prices in Eqs. (11) and (12),

$$\begin{aligned}
MS_1^{ww} &= m \\
MS_1^{wa} &= \frac{m\bar{s}}{m\bar{s} + (u-p_2^{wa})(1-a)(1-m)} \\
MS_1^{aw} &= \frac{am(u-p_1^{aw})}{am(u-p_1^{aw}) + (1-m)\bar{s}} \\
MS_1^{aa} &= \frac{am(u-p_1^{aa})}{am(u-p_1^{aa}) + (u-p_2^{aa})(1-a)(1-m)},
\end{aligned}$$

and the market shares of niche products are given by $MS_2^c = 1 - MS_1^c$ in all cases. It can be shown that $MS_1^{aw} < MS_1^{ww} < MS_1^{aa} < MS_1^{wa}$ always holds. Inspection of index H as a function of equilibrium market shares MS_1^c and MS_2^c across the four market configurations yields the following result.

Proposition 2. *Equilibrium sales concentration across the four market configurations when mainstream products outsell niche products satisfies $H^{aw} < H^{ww} < H^{aa} < H^{wa}$. An increase in the value of WOM that preserves the sales ranks of products can trigger:*

(I) *A configuration shift from AW to WW, which incorporates mainstream consumers into WOM and increases the concentration of sales generating a superstar effect.*
(II) *A configuration shift from WA to WW, which incorporates niche consumers into WOM and reduces the concentration of sales generating a long tail effect.*

[11] I restrict the analysis to the case of empirical interest where mainstream products outsell niche products in equilibrium. The review of the empirical literature in Section 1.1 suggests that, despite shifts in sales concentration, products in the head of the sales distribution significantly outperform those in the tail before and after observed shifts (i.e., sales ranks are preserved). In the model, niche products can outperform mainstream products in configuration AW when both m and a are low. In that case, it can be shown that $H^{aw} > H^{ww}$ if $MS_1^{aw} \ll MS_2^{aw}$. A configuration shift from AW to WW then reduces the concentration of sales and reverses the sales rank of mainstream and niche products, implying that the superstar effect in Proposition 5 is no longer present. The long tail effect continues to hold, however.

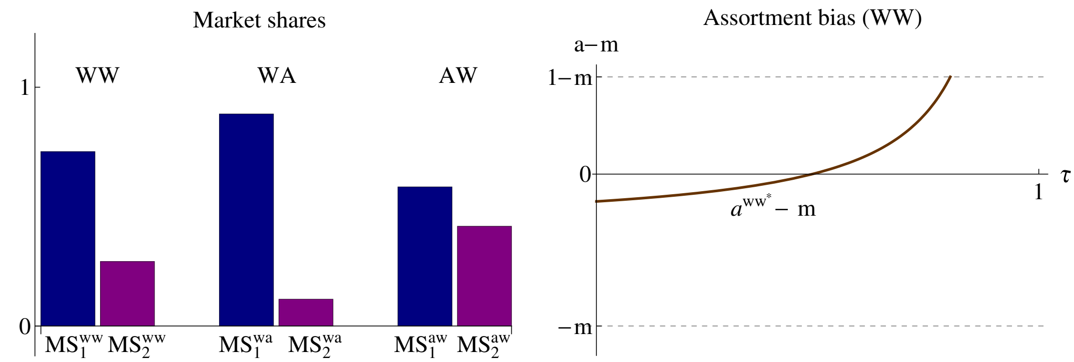

Fig. 4. On the left, market shares of mainstream and niche products in the three market configurations with word of mouth. A configuration shift from WA to WW reduces the concentration of sales generating a long tail effect. On the right, the firm's optimal assortment composition bias in configuration WW. The higher the degree of preference matching, the higher the weight of mainstream products in the assortment.

The result explains how efficiency improvements in WOM trigger shifts in the concentration of sales. Recall that only one consumer type participates in WOM when its value is low (market configurations WA and AW) but both types participate when it is high (configuration WW). Thus an increase in the value of WOM can incorporate new consumer types into the process. Proposition 2 shows that incorporating mainstream consumers (shift from AW to WW) increases the relative sales of mainstream products, and this increases the concentration of sales within the assortment. Incorporating niche consumers into WOM (shift from WA to WW) increases the relative sales of niche products, which reduces the concentration of sales. The left panel in Fig. 4 plots product market shares in these configurations to illustrate the result.

The mechanisms predicted by the model contribute to explain the empirical evidence on lower sales concentration in online retail. The literature reviewed in Section 1.1 finds that sales concentration is lower in the online channel than in the offline channel, that online recommender systems contribute to this effect, and that online WOM has a larger impact on niche consumers. The model can reconcile these findings. The firm profits from increasing the value of WOM for consumers, and thus online retailers have incentives to facilitate the provision of product recommendations on their websites and implement recommender systems. This benefits niche consumers the most, because it mitigates the population advantage enjoyed by mainstream consumers in offline WOM. As a result, niche consumers participate more in the market and the firm adjusts prices accordingly, which reduces the concentration of sales generating a long tail effect.

The result is closely related to Bar-Isaac, Caruana, and Cuñat (2012) and Yang (2013). These papers also contribute theoretical search foundations to explain lower sales concentration in online retail. In both cases, the authors analyze the interaction between consumer search strategies and the variety of products supplied in the market. Bar-Isaac et al. (2012) show that lower consumer search costs can drive firms to supply rare product designs, and Yang (2013) shows that improvements in consumer search, either through lower search costs or better targetability, can drive firms to produce less popular product varieties that would otherwise remain unavailable. Both effects reduce the concentration of sales in the market. The argument developed here focuses on consumer interactions during search while keeping the supply of products fixed. This explains the concentration shifts observed within firms that supply identical product assortments through both online and offline retail channels. Nonetheless, the three mechanisms are complementary. Taken together, the findings suggest that improvements in consumer search targetability and product recommendations together with supply-side changes in product design and availability all contribute to the long tail phenomenon.

The model also shows that WOM improvements that benefit mainstream consumers the most increase the concentration of sales. This generates a superstar effect, reinforcing bestseller products. The result can be reconciled with the empirical evidence on popularity feedback mechanisms (e.g., bestseller charts), which have been shown to benefit best-selling products in the head of the sales distribution. Salganik, Dodds, and Watts (2006) study demand over a set of rare songs offered to test subjects on the Internet, and Tucker and Zhang (2011) analyze the click-through rates of a webpage indexing marriage agencies. In both cases popularity feedback increases concentration and consumer participation, as is the case of the superstar effect here.

6. Optimal assortment composition

The model assumes by construction that both mainstream and niche products are supplied, but the firm can alter their weight in the assortment or the prominence with which they are displayed. When the efficiency of WOM increases, as is the case in online retail, should the firm increase the weight of niche products in its assortment or promote mainstream products instead? To answer this question, I examine the firm's optimal assortment composition when both consumer types search with WOM.[12]

I incorporate the assortment choice into the timing of the game. Consider the game where the firm chooses assortment composition a in the first stage, sets prices p_1 and p_2 in the second stage, and consumers search the assortment and search with WOM in the third and fourth stages, respectively. I restrict the analysis to market configuration WW and the cases where an interior solution for a is well defined. Consumer search strategies and optimal prices carry over from the preceding analysis, so I proceed to solve the firm's assortment choice in the first stage given the firm's profit frontier π^{ww^*}. Denote the firm's optimal assortment composition in this market configuration by a^{ww^*}. Inspection of first-order condition $\partial\pi^{ww^*}/\partial a = 0$ identifies two candidate solutions. The second-order condition reveals that only the following is a maximum,

$$a^{ww^*} = \frac{(1-m)\left(2m-\tau^2\right) + \sqrt{(1-2m)^2(1-m)m\tau^2}}{4(1-m)m-\tau^2},$$

[12] The model provides an interior solution for a in market configuration WW, which is the configuration most relevant to online retail. Unfortunately, other market configurations yield only corner solutions for a. Fully endogenizing assortment composition across all configurations is a complex problem which requires a richer model specification to account for the availability of different product types, and is beyond the scope of this paper.

and $a^{ww^*} \in (\frac{1}{2}, 1)$ so that the firm chooses an interior solution when $\tau < \hat{\tau}$ where

$$\hat{\tau} = \sqrt{\frac{1-m}{m}}.$$

Otherwise the firm chooses a corner solution because $a^{ww^*} \geq 1$.

Proposition 3. *The firm's optimal assortment composition when both consumer types search with WOM (market configuration WW) and preference matching is not very high, $\tau < \hat{\tau}$, is given by a^{ww^*}. This implies that the firm over-represents niche products in the assortment relative to the consumer population's preferences when preference matching τ is low, and over-represents mainstream products when it is high.*

WOM presents the following tradeoff for the firm choosing the composition of its assortment. Increasing the share of one product type in the assortment reduces the search costs incurred by consumers of that type at the expense of increasing the search costs incurred by the other type. For example, an increase in the share of mainstream products increases the odds for mainstream consumers searching the assortment, which in turn increases the provision of recommendations by mainstream consumers (higher β_1 and α_1^{ww}). This results in lower search costs for mainstream consumers and higher search costs for niche consumers (due to lower β_2 and α_2^{ww}). The firm's tradeoff is as follows. On the one hand, mainstream consumers generate most of the firm's sales. On the other hand, niche consumers incur higher search costs due to their WOM disadvantage. So increasing the share of mainstream products in the assortment provides a small search cost reduction for the large mass of mainstream consumers at the expense of a larger search cost increase for the smaller mass of niche consumers.

The firm's solution hinges on the degree of preference matching τ, which determines the comparative WOM advantage of mainstream consumers over niche consumers. The right panel in Fig. 4 illustrates the result. When the degree of preference matching is low, the firm over-represents niche products in the assortment relative to the share of niche consumers in the population ($a^{ww^*} < m$), because reducing niche consumer search costs has the largest impact on profits. When the degree of preference matching is high, the firm chooses instead to over-represent mainstream products in the assortment ($a^{ww^*} > m$) because in this case reducing the search costs of mainstream consumers has the largest impact.

The result suggests that the long tail effect should not drive the firm to focus on niche products, at least not at the expense of mainstream products. Though improvements in the efficiency of WOM increase the relative sales of niche products in the tail of the sales distribution, mainstream products in the head of the distribution still account for most of the firm's revenues. Moreover, the search improvements that lead niche consumers to more easily locate their preferred products also reduce the downsides of promoting mainstream products. Therefore, even as the market share of niche products increases, the firm is better off promoting mainstream products instead.

7. Managerial implications

I next summarize the managerial implications of the analysis. I use a causal loop diagram to represent the logic of value creation and appropriation by the firm in the presence of consumer WOM, following the methodology proposed by Casadesus-Masanell and Ricart (2010). Fig. 5 provides the representation. Underlined elements are choices made by the firm, and non-underlined elements are consequences. Arrows connect causes with consequences to identify positive feedback loops. Dashed arrows identify negative feedback loops. Elements inside a box are rigid consequences or stocks, which accumulate over time and change slowly in response to the feedback loops that cause them.

The representation describes the implications of WOM for the firm's business model in the presence of the long tail effect (market configuration WW). The logic is best illustrated with an online retailer, so consider the case of Amazon discussed in the introduction. Focusing on the firm's choices in the lower part of the diagram, Amazon provides personalized recommendations on its storefront and product pages, which increases the value of WOM on its store compared to offline interactions (reduces w and increases τ). As shown in the analysis, a consequence of this choice is lower sales concentration within the assortment compared to offline retail channels (configuration shift to WW which benefits niche consumers). Amazon also chooses to promote mainstream products on its storefront (high τ suggests that high a must be optimal). The previous choices jointly contribute to lower consumer search costs, and this increases sales volume. In turn, higher sales volume and lower sales concentration provide Amazon with more consumer feedback about more products through browsing activity, ratings, and reviews (consumers of both types provide recommendations in configuration WW). This point is important, because Amazon depends on consumer feedback to feed its recommender system and supply personalized product recommendations, which closes the two loops around "consumer feedback."

The two loops described are in fact virtuous cycles, because Amazon accumulates a larger stock of consumer feedback over time. Although the model is static, it should be clear that this can be a source of competitive advantage for the firm versus competitors that do not exploit WOM, or have been slower to do so. By iterating over these cycles Amazon accumulates a larger stock of consumer feedback, creating more value for its customers and becoming the "go to" place for them to discover products that match their taste. This reinforces Amazon's choices to feature product recommendations and promote mainstream products.

Amazon sets high prices to appropriate the value it generates through lower search costs. Note however that there are two sources of tension (or negative loops) the firm needs to manage carefully. The first one relates to pricing. The firm prices to appropriate consumer

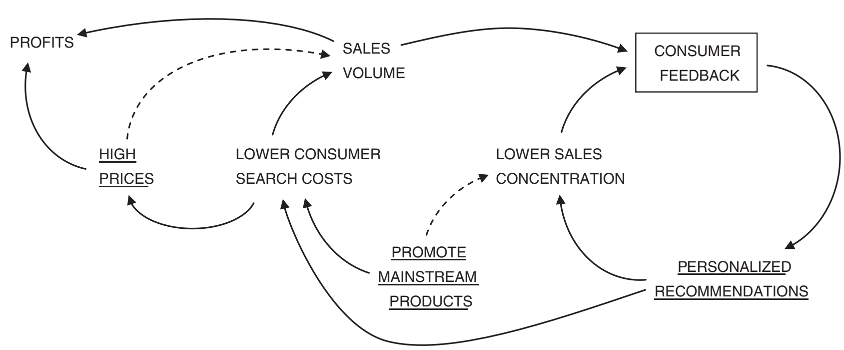

Fig. 5. The implications of the analysis for the firm's business model. Underlined elements identify the choices of the firm and non-underlined elements are consequences. Arrows connect causes with consequences.

surplus, but does so ensuring that consumers with high sampling costs who rely on WOM remain willing to participate (optimal prices ensure that $\mu_1^w = 0$ and $\mu_2^w = 0$ in configuration WW). That is, the firm strikes a balance between high prices and the sales volume derived from WOM. The second source of tension relates to the prominence of mainstream products. Promoting mainstream products benefits mainstream consumers but hurts niche consumers (higher β_1 and α_1^{ww} but lower β_2 and α_2^{ww}). So the firm also needs to strike a balance between promoting mainstream products and the demand for niche products in the tail of the sales distribution.

8. Concluding remarks

I have analyzed the role of WOM for consumer product discovery in horizontally differentiated product categories. The results can be summarized by noting that the exchange of product recommendations reduces consumer search costs, but those with less prevalent preferences and the products that appeal to them benefit less due to the mechanisms underlying traditional WOM interactions. The online environment provides an opportunity for the firm to facilitate WOM and implement recommender systems, which benefits all consumers but has a larger impact on those with less prevalent preferences. This increases the market share of niche products in the tail of the sales distribution, reducing the concentration of sales within the firm's assortment. Improvements in online WOM therefore contribute to explain the long tail phenomenon.

Firms with lower inventory costs stand to benefit the most from the long tail effect. These firms can increase the depth of their assortment beyond that of competitors, ensuring that they are well positioned to serve the demand for niche products in the tail of the sales distribution. So online retailers pioneering the implementation of recommender systems have also increased the value of stocking a deeper assortment than brick and mortar competitors. The analysis suggests caution against excessive focus on niche products, however. Because the online environment facilitates product discovery and mainstream products contribute the most to sales volume, the firm is better off responding to the long tail effect by increasing the prominence of mainstream products. In fact, the firm can profit from over-representing mainstream products in the assortment relative to their potential customer base.

The implications of the findings for competition are worth stressing. Firms with a large customer base will profit the most from online WOM and recommender systems. These systems benefit from a large stock of consumer feedback to improve their accuracy and exhibit a learning curve to identify the preferences of new customers. Consumers will receive less accurate recommendations when switching purchases across firms and, in general, when patronizing smaller firms. Both factors suggest that the firm can exploit consumer WOM to grow its customer base and outperform competitors over time.

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