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A Theory of the Long Tail

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Word of Mouth and Taste Matching: A Theory of the Long Tail*

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Abstract

I present a model to assess the impact of demand-side factors on the concentration of sales within large product assortments. Consumers face a search problem within an assortment of horizontally differentiated products supplied by a monopolist. They may search for a product match by drawing products from the assortment or by seeking word of mouth recommendations from other consumers. Product evaluations prior to purchase and word of mouth are shown to arise endogenously, and increase the concentration of sales. I show that taste matching mechanisms such as recommender systems, which allow consumers to obtain product recommendations from others with similar preferences, reduce sales concentration by generating a long tail effect, an increase in the tail of the sales distribution. Insights are derived on the mechanisms driving concentration in artistic markets and their strategic implications for the firm. The model is suited for experience good markets such as music, cinema, literature and video game entertainment.

Keywords: Search, Word of Mouth, Sales Concentration, Long Tail

JEL Classification: C78, D42, D83, L15, M31

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1 Introduction

The expansion and development of electronic commerce in recent years has brought radical change to the distribution landscape. Products previously limited to specialized stores are now only clicks away from delivery, offering consumers access to a larger variety of goods than ever before. This evolution has been most noticeable in product categories such as books, music and films, where assortment sizes have increased dramatically. For example, Amazon sells over 3 million book titles compared to the 100.000 stocked by an average Barnes & Noble store.[1] The digitalization of content paired with the advent of digital distribution is further fueling this trend. Observers and industry analysts have proposed that online distribution will increase the market share of products catering to niche audiences, increasing their participation in the sales mix with respect to the traditional distribution channel. This phenomenon was coined by Anderson [3] as the *long tail*, referring to the increase in the tail of the sales distribution. As empirical studies turn their attention to the available data and the mechanisms driving these changes are discussed, the long tail has become an object of academic debate.

Increased availability of products is understood to be the explanatory factor for this phenomenon, given that more niche consumers can now access their preferred products through the online channel. Some of these transactions were previously excluded from the market due to the logistical constraints of traditional distribution, which limited the availability of products with a low market share. However, recent studies suggest that factors beyond availability are driving down sales concentration. Brynjolfsson et al. [7] analyze the sales distribution of a clothing retailer offering the same product selection across two separate channels: catalog and online. Both channels offer equal prices and conditions. Considering consumers that purchase through both channels, they find that sales concentration is lower online. In another study, Elberse and Oberholzer-Gee [12] report decreasing sales concentration within a sample of video titles over a five year period. Their data source covers both online and offline retail channels. By controlling for the introduction of new titles in the market, they conclude the changes observed are driven by demand side effects and online retailing. Both studies suggest that the online channel is triggering changes in consumption

[1] See Brynjolfsson et al. [8].

patterns, but the drivers of these changes are not well understood.

This paper presents a model that can rationalize these facts. Our approach is motivated by the impact of the Internet on consumers' product discovery process. The Internet is increasingly enabling consumers to locate and interact with others that share their product taste, with independence of geographical distance and the prevalence of their taste in the population. Our model explains how improved taste matching reduces the concentration of sales. The result stems from modeling word of mouth processes, the direct exchange of product recommendations among consumers. We show that word of mouth benefits mass market products and mainstream consumers the most. Product market shares, on the one hand, enjoy increasing returns to appealing to a larger share of the consumer population. The benefits derived by consumers, on the other hand, exhibit increasing returns to the prevalence of their taste in the population. Both asymmetries dissipate when taste matching is introduced in the word of mouth process, increasing the efficiency of the information exchange and reducing the concentration of sales.

Mechanisms improving taste matching are pervasive online. Search engines, message boards, fan communities, peer-to-peer file sharing networks and social networks allow consumers to easily locate others that share their taste in order to discover new products. Our model explains how taste matching reduces search costs in the market, increasing consumer participation and firm profits. Major online retailers have seized this opportunity by deploying recommender systems in their storefronts. These systems automate the matching process by generating personalized recommendations for consumers (e.g. 'customers who bought this item also bought...'). This is achieved by processing data on consumer preferences retrieved, for example, from product purchase and browsing history, product ratings and consumer demographics. While the development of these technologies has been pioneered by online retailers, other market participants with access to consumer data such as traditional retailers and financial intermediaries are following. By better exploiting consumer information to provide valuable product recommendations, firms can sustain a competitive advantage.

To the best of our knowledge, no previous theoretical work has explored the link between word-of-mouth and sales concentration. We consider a market of horizontally differentiated products supplied by a monopolist at a common price. The monopolist may be an electronic retailer or content provider offering a large product assortment. Consumer preferences partition the product space into preferred and non-preferred products, and consumers only derive utility from the consumption of the former. But consumers arrive to the market uninformed and cannot identify their preferred products within the assortment. All products are ex-ante identical, and the value of each product can only be determined by sampling it. A product *match* is achieved when a consumer locates a product which belongs to her preferred set. But sampling products is costly, as it requires time and attention, and thus consumers face a search problem to locate relevant products.

To enrich the demand side of the market, we let consumers differ in their product preferences and sampling costs. Consumers search for a match by sampling products, and may either draw products directly from the assortment or seek word of mouth recommendations from others. When consumers draw from the assortment, we show that improved product exploration increases the concentration of sales. That is, improving consumers' ability to sample products and better inform their purchases cannot explain the long tail.

Consumers seeking recommendations learn from the population of consumers that already located a match by drawing products from the assortment, and we find that consumers choose to seek and follow recommendations because they increase their probability of locating a product match. Mainstream consumers, those whose preferences are more prevalent in the population, benefit more from word of mouth because recommendations are more likely to originate from others that share their taste, thus enjoying a larger probability of locating a match. Niche consumers with less prevalent preferences benefit less, and may not seek recommendations. We then introduce a taste matching mechanism that allows consumers to obtain recommendations from those that share their preferences. We show that matching improves the probability of locating a match for all consumers, yielding a larger benefit to niche consumers and reducing the concentration of sales as a result.

The construction is well suited for experience goods such as music, films, books or video games. The satisfaction derived from these products is hard to anticipate; it can be argued that however informed a consumer may be on the objective characteristics of a product, such as genre, characteristics or plot, personal judgment requires direct exposure. Furthermore, due to exogenous factors beyond those explored here, price dispersion across titles is generally low in these markets. Hence market shares are largely determined by consumers' taste rather than differences in price.

1.1 Literature

Little theoretical work has focused on the mechanisms driving sales concentration within product assortments. Product differentiation models, for example, cannot readily explain how changes in the distribution channel or the information structure affect the composition of sales. The search literature has mainly focused on price dispersion, by considering homogeneous goods offered by different sellers. These models are suited for settings where price dominates the search, but provide no insights on sales concentration across heterogeneous products. Some instances have explored heterogeneous consumer preferences with location models, such as Bakos [6]. But in this case the equilibrium is symmetric for all consumer types and sellers, and no sales concentration is predicted by the model.

Recent work related to the long tail debate has proposed several factors that may explain sales concentration. Brynjolfsson et al. [7] present a search model with advertising. Consumers arrive to the market informed about advertised products, but incur search costs to learn about the remaining. Sales concentration depends on how the size of the advertised and non-advertised product pools compare. Product popularity information is analyzed in an experiment by Salganik et al. [17]. They study demand concentration over a set of rare songs offered to test subjects on the Internet, with some treatments including popularity feedback and others not. They find that popularity information increases both concentration and the unpredictability of popularity in the outcome. Tucker and Zhang [19] analyze a dataset containing the click-through rates of a webpage indexing marriage agencies, both when popularity is reported to users and when it is not. They find that both concentration and consumer participation increase when popularity information is provided. However, it is unclear to what extent advertising and product popularity information can explain lower sales concentration. Since these factors have been shown to increase concentration, a reduction in concentration would require consumers to be less exposed to both, making for an unclear case in the online channel.

More closely related to the mechanisms explored here, Fleder and Hosanagar [13] analyze the impact of recommender systems on sales concentration. In their analytical model, they consider consumers that arrive sequentially to the market and realize random purchases or follow product recommendations given an exogenous probability. The recommender system implements a popularity rule, recommending the bestselling product based on the purchases of past consumers, and they show that the process tends to increase the concentration of sales. As a result, the treatment is somewhat akin to providing product popularity information. Unlike our approach, it does not account for the underlying preferences of consumers nor their incentives to engage in word of mouth processes and follow recommendations.[2]

Our approach focuses on the demand for recommendations and their impact on sales, and we assume that recommendations are readily supplied by informed consumers in the market. A large body of literature has documented several motivations for consumers to contribute to word of mouth processes, see Dellarocas [10] for a related discussion. Avery et al. [5] explore reward mechanisms for the optimal provision of recommendations. In our model, consumers providing recommendations derive no direct benefit (nor cost) in the process, but benefit indirectly from lower prices. Although consumers demanding recommendations are willing to reward those that provide them, we do not further explore this dimension of the problem. Casual evidence suggests that recommendations are well provisioned in the markets considered here. Consumers may enjoy the opportunity to discuss their preferred entertainment products with others. The existence of such positive network effects on the demand side of artistic markets was proposed by Adler [1] and may well offset any bargaining opportunity.

Artistic markets exhibit highly concentrated sales distributions with a minority of bestselling titles. The phenomenon is widely acknowledged in music, cinema and books, and has sometimes been referred to as 'hit culture'. A series of papers in the economics literature have analyzed these markets, pioneered by Rosen's [16] famous superstars model as well as later contributions, such as MacDonald [14]. This literature has, for the most part, explained the phenomena by assuming a dispersion of talent among producers; greater talent commands higher profits and market shares than lesser talent. While this approach provides valuable insights on artistic markets, it is unclear that talent alone can explain the distribution of sales. Consumers generally acknowledge that differences in talent are important, yet they have a hard time describing what defines talent or evaluating it. Artistic quality may not be measurable independently of taste. Producers widely

[2] Additional results are provided with simulations where consumers and products are located on a 2-axis space. In this setting, the recommender model is richer and consumer preferences are well defined. In most of the scenarios considered, concentration tends to increase.

recognized as talented do not appeal to all consumers, while lesser talented artists generally have a niche audience of followers. Our analysis suggests that mainstream appeal and the added effects of search costs may well be an alternative route to stardom.

The paper is organized as follows. The next Section introduces the building blocks of our search model. In Section 3 we start with the simplest instance of search, where there is no word of mouth and consumers cannot evaluate products before purchase. We then proceed to enrich search strategies in steps to isolate their impact on the market. In Section 3.1 we introduce evaluations and allow consumers to learn the utility they derive from products before purchasing them. Starting in Section 4 we introduce word of mouth in the model, and let consumers seek product recommendations from others. In Section 4.1 we analyze the impact of taste matching on the word of mouth process. Section 5 concludes.

2 The model

Consider a market where a monopolist supplies an assortment of horizontally differentiated products. The assortment consists of a continuum of product varieties of measure one. The monopolist quotes a common price p for all products in the assortment and incurs a transaction cost t per unit sold. The single price restriction implies that the monopolist cannot price discriminate consumers or products, and will allow us to isolate demand-side effects driving sales concentration.[3]

In this market there is a unit mass of consumers. Preferences over products are simplified to a binary classification; a consumer may derive positive utility from a product or not. In the first case, the consumer derives utility u from consumption. In the second case, the consumer derives zero utility from the product. Consumers exhibit unit demand, and although they may derive utility from several products they will only consume one.

Consumers are heterogeneous in their product preferences, and we take the view that the most significant difference across consumers is their selection of preferred products. In particular, we assume that all consumers agree on some products, which exhibit universal appeal, but differ in their remaining subset of preferred products. We consider $T \geq 3$ consumer types, and partition the

[3] Price dispersion may allow prices to signal product appeal to consumers, enabling consumer search strategies based on the informational content of prices. Our model is better suited to a scenario where prices are not informative.

product space into $N = T+1$ product pools. We let consumers of type t prefer products pertaining to product pools t and N. So products in pool N are mass market products, while products in pools $t \in (1, T)$ appeal only to a subset of the population. For simplicity, we assume that product pools are of equivalent size, so the measure of each product pool within the product space is $1/N$.

We will refer to T as a measure of *taste fragmentation*, since the larger the value of T, the more differentiated the product space is for consumers. It is important to stress that the purpose of this partition is to define preferences, and there is no discernible product characteristic that allows an uninformed consumer to identify product pools within the assortment.

The analysis is of interest when consumer types differ in their prevalence in the population, and we denote by s^t the share of consumers of type t. Without loss of generality, we order types in increasing prevalence, where $s^1 < s^2 ... < s^T$. Thus consumer types become mainstream in t (or less niche), as their preferences are more widespread in the population.

When entering the market, consumers observe the level of prices p and taste fragmentation in the population, T. However, they arrive uninformed about products and cannot identify their preferred products within the assortment. All products are ex-ante identical, and as a result consumers face a search problem in order to locate a preferred product.

A consumer can become informed about products by sampling them. A product *match* is achieved when a preferred product is identified. Sampling products is costly, and we let sampling costs be uniformly distributed in the consumer population independently of product preferences, where the cost of consumer i is given by $c^i \sim U[0, \bar{c}]$. Thus sampling a product which does not yield a match incurs disutility c^i, and sampling and consuming a product match yields utility $u - c^i$. Consumers always incur a sampling cost before deriving utility from a product. For experience goods, this can be understood as the time investment required to experience the good.

Consumers form a rational expectation of their participation costs in the market. Participation costs have two components: the search costs to locate a match and the price to be paid for the desired product. Consumers may participate in the market to purchase and consume a preferred product or remain out. Utility of the outside option is normalized to zero.

To summarize our model:

- There are $N = T + 1$ product pools in the assortment, and all products are priced at p.

- There are T consumer types, and consumers of type t derive utility u from products in pools t and N, and zero from the remaining.
- The share of consumers of type t in the population is given by s^t, where $s^t < s^{t+1}$.
- Sampling costs are uniformly distributed in the consumer population, $c^i \sim U[0, \bar{c}]$.

The search problem is solved assuming uniform sampling from the product space. This is consistent with the fact that products are ex-ante identical for consumers. We assume sampling costs in the consumer population $\bar{c}$ are sufficiently high to avoid corner solutions in the pricing game, ensuring a positive mass of consumers does not to participate in equilibrium and the market remains uncovered.[4] All games are solved by backwards induction.

We refer to *search costs* as the average cost incurred by participating consumers to locate a product match in the market. We will show that search costs and the demand for each product pool (or the products contained therein) depend on the search strategies available to consumers. A *sales distribution* assigns to each product pool a market share, which is obtained by dividing demand for that pool over the aggregate demand across all pools. When analyzing the impact of different search strategies on the market, the sales distribution allows us to isolate variations in the concentration of sales (or market share variations) from volume effects driven by shifts in consumer participation.

To analyze variations in the concentration of sales across sales distributions, we require only the following property. Consider an ordering of product pools in decreasing market share order, such that the product pool with rank 1 has the highest market share and the rank N pool has the lowest. A market share transfer from a low rank pool to a higher rank pool that preserves the ranks reduces concentration. Conversely, a rank-preserving transfer from high to low rank pools increases concentration. All concentration indexes in the literature satisfy this property, including for example the Gini index.

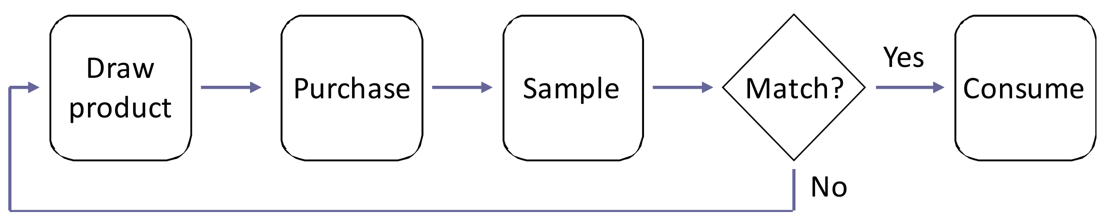
Finally, consider the impact of a concentration shift on the sales distribution. A rank-preserving transfer that reduces concentration by increasing the market shares of high rank pools implies a growth in the tail of the distribution (loosely defined). We denote such transfer as a *long tail effect*.

[4]This requires $\bar{c} > \frac{1}{2}(u - t - r)$ throughout our analysis, where r is the cost of seeking a recommendation as introduced in Section 4.

3 Search with no word of mouth

We start with the simplest instance of our model, the case in which there is no word of mouth and consumers cannot evaluate products prior to purchase. In this setting, consumers can only become informed about products by purchasing them. With this approach, we can analyze the impact of evaluations prior to purchase by separately introducing them in the next Section. While consumers stand to benefit from evaluating products before purchasing them, note that their ability to do so is largely under the monopolist's control, for instance by setting retail policies or publishing product previews. The impact of evaluations is of interest because it has been suggested that improved exploration in the online channel, provided for instance by book excerpts or audio clips, could generate a long tail effect.

Consider the following two-stage game without evaluations. In the first stage, the monopolist chooses the price level in the market, p. In the second stage, consumers may search for a match by sequentially drawing and purchasing products from the assortment. Consumers incur price p and sampling cost c^i on each draw. Product evaluations prior to purchase are not allowed, so consumers can only sample and become informed about products by purchasing them first. The following graph depicts the sequential search process faced by consumers:



Consumer search strategy. Consider the search problem faced by consumers in the second stage given a price level p. The only feasible search strategy is to sequentially purchase and sample products until a match is located. Denote by β the match probability for a consumer on each draw. A consumer of type t will only obtain a product match when drawing a product from pools t or N. Since products are drawn uniformly from the assortment, the probability of drawing from any given pool is $1/N$. Hence,

$$\beta = \frac{2}{N}, \tag{1}$$

and each purchase is a Bernoulli trial with success probability β, which is common for all consumers. The expected utility of a new purchase for a consumer i with sampling cost c^i is

$$u_s^i = \beta u - c^i - p, \tag{2}$$

given that utility u is only derived with probability β but price p and sampling cost c^i are incurred on each purchase. The expected utility of a purchase does not depend on a consumer's type, but will vary across consumers depending on their sampling cost c^i. The utility of a successive draw, however, is constant throughout the search for any given consumer. Hence a consumer either searches until a match is obtained or does not participate in the market. We can identify the consumer of each type which is strictly indifferent between both alternatives by equating u_s^i to zero. Denote this indifferent consumer by c_s^i,

$$c_s^i = \beta u - p. \tag{3}$$

Only consumers with a sampling cost $c^i \leq c_s^i$ choose to search, and participation is homogeneous across types. Consumers with a higher sampling cost prefer not to participate in the market. The search process for any consumer finalizes once a match is located; searching for a second match cannot be optimal given that product prices are homogeneous and search is costly.

Sales concentration. We next characterize the distribution of sales across products. A participating consumer may purchase several non-preferred products until a match is located, due to failed draws during her search, but will only purchase a single preferred product. Denote by D_p and D_{np} a consumer's expected demand for preferred and non-preferred product pools respectively. The probability of purchasing a non-preferred product on each draw is given by $1 - \beta$. The probability of purchasing j non-preferred products before purchasing a preferred product is given by $(1-\beta)^j\beta$. If we consider all possible search histories, and given that each consumers has two preferred product pools,

$$D_p = \frac{1}{2}\sum_{j=0}^{\infty}(1-\beta)^j\beta = \frac{1}{2}. \tag{4}$$

And since there are $N-2$ non-preferred product pools, the expected demand for each of these pools is

$$D_{np} = \frac{1}{N-2}\sum_{j=0}^{\infty} j(1-\beta)^j\beta = \frac{1}{2}. \tag{5}$$

So $D_p = D_{np}$, and each participating consumer's demand for preferred and non-preferred products pools coincides. Hence the sales distribution is uniform, and the concentration of sales is minimum.

Firm pricing. We next turn to the first stage of the game and solve the firm's problem. The consumer participation constraint for all types (3) is a function of price level p. Note that for the firm to sustain positive prices and face demand, so that $c_s^i > 0$, we require $t < \beta u$. If the monopolist's transaction costs are high or taste is very fragmented (high T), then $t \geq \beta u$ and no feasible transaction is profitable, so the market breaks down. We need only consider the case where $t < \beta u$. Given that search is a Bernoulli process and each trial has success probability β, the expected number of purchases a consumer requires for a match is β^{-1}. So consumers of all types with $c^i \leq c_s^i$ participate in the market and each consumer executes β^{-1} purchases on average. Firm profits given the aggregate demand for all product pools are

$$\pi_s = \frac{c_s^i}{\bar{c}}\beta^{-1}(p-t) = \frac{(u\beta - p)(p-t)}{\bar{c}\beta}. \tag{6}$$

Solving for the firm's optimal price we obtain

$$p_s = \frac{u\beta + t}{2}. \tag{7}$$

Social welfare. We next derive social welfare SW_s, defined as the sum of consumer surplus and firm surplus. Every participating consumer generates social surplus u net of the transaction and sampling costs involved in the search. Since every consumer purchases on average β^{-1} products to locate a match,

$$SW_s = \frac{c_s^i}{\bar{c}}(u - \beta^{-1}t) - \int_0^{c_s^i} \beta^{-1}c^i dc^i. \tag{8}$$

Proposition 1 *When consumers cannot evaluate products prior to purchase, the distribution of sales is uniform and sales concentration is minimum. Furthermore, the market breaks down if transaction costs are high or taste is very fragmented.*

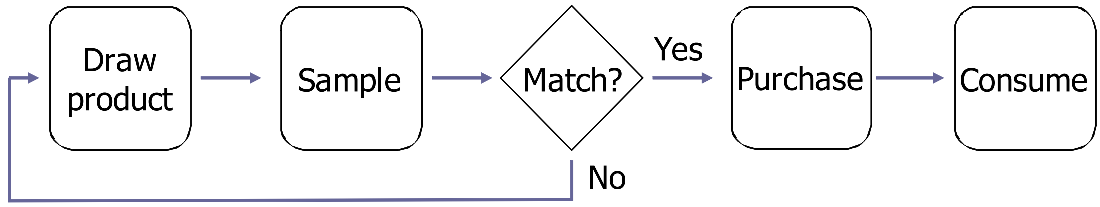
As shown by this first result, all product pools enjoy an equal market share when no product evaluations prior to purchase are allowed. Due to the unsuccessful purchases incurred by consumers to locate a match, every participating consumer exhibits uniform demand (in expectation) over all product pools. If product pools that appealed to no consumer were present in the assortment, they would enjoy an equal market share to the rest. Thus market shares are not informative of consumer preferences.

Demand is downward sloping in prices, as expected. Consumers anticipate the costs of locating a match, which requires incurring unsuccessful purchases, and do not participate in the market if it does not pay off. The firm recognizes this and discounts prices by β, the match probability faced by consumers on each draw from the assortment, which determines their willingness to participate. In addition, when taste is very fragmented or transaction costs are high, the market breaks down. In these cases, no profitable price for the monopolist faces positive demand in the market. Similar findings were reported by Bakos [6] in a search model with horizontally differentiated products.

3.1 Evaluations

We next consider the two-stage game with product evaluations prior to purchase. In the first stage, the monopolist chooses the price level in the market, p. In the second stage, consumers may search for a match by sequentially drawing and sampling products from the assortment. Since consumers can sample products before purchase, they incur sampling cost c^i on each draw but will only execute a purchase at price p when they locate a match. Note that consumers strictly prefer to sample products before purchase whenever possible, as this avoids unsuccessful purchases.[5] Consumers now face the following sequential search process:

[5] Our model of evaluations is equivalent to a market where consumers can realize costless returns before consumption.



Consumer search strategy. Consider the consumer's problem in the second stage given a price level p. The probability of a match when drawing and sampling a product is given by β. The expected utility of a new product evaluation for an unmatched consumer is

$$u_e^i = \beta(u - p) - c^i, \tag{9}$$

given that consumers only purchase if a match is located but incur sampling cost c^i on every draw. The expected utility does not depend on a consumer's type, but will vary across consumers depending on their sampling cost. The utility of a successive draw, however, is constant throughout the search for any given consumer. Hence we can identify the consumer of each type which is strictly indifferent between evaluating products and not participating by equating u_e^i to zero. We denote the indifferent evaluator by c_e^i,

$$c_e^i = \beta(u - p). \tag{10}$$

Only consumers with a sampling cost $c^i \leq c_e^i$ choose to search, and participation is homogeneous across types. Consumers with a higher sampling cost prefer not to participate in the market. The search process for any consumer finalizes once a match is located; searching for a second match cannot be optimal.

Sales concentration. Next we characterize the sales distribution with evaluations, denoted by σ. Let s_e^t be the share of consumers of type t among the mass of consumers that search with evaluations. We proceed by characterizing separately the sales distribution generated by each consumer type σ^t, where $\sigma_n = \sum_t s_e^t \sigma_n^t$.

To characterize σ^t, note that consumers only purchase when they locate a product match, so the sales distribution generated by consumer of type t must equal their distribution of matches over products. Note that all consumers of type t are identically and independently distributed in the sampling outcome, as every product evaluation is independent of past evaluations and those of other consumers. Thus σ^t is independent of the market participation of consumers of type t, and we can derive σ^t by characterizing the distribution of matches over products for a single evaluation of a consumer of type t. To do so, it is useful to define indicator function λ based on consumer preferences. Let $\lambda_n^t = 1$ if $n = t$ or $n = N$, and $\lambda_n^t = 0$ otherwise. The probability that a consumer of type t matches product n is equal to $(1/N)\lambda_n^t$, and the probability of a match over all products is given by β. This implies

$$\sigma_n^t = \frac{(1/N)\lambda_n^t}{\beta} = \begin{cases} \frac{1}{2} & \text{if } n = t \text{ or } n = N \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

We can now derive σ,

$$\sigma_n = \sum_t s_e^t \sigma_n^t = \begin{cases} \frac{s_e^t}{2} & \text{if } n \in (1, N-1) \\ \frac{1}{2} & \text{if } n = N \end{cases} \tag{12}$$

And since participation is homogeneous across all consumer types, $s_e^t = s^t$ and the market share of product pools is increasing in n. Hence introducing evaluations prior to purchase strictly increases the concentration of sales in the market.

Firm pricing. We next turn to the firm's problem given the consumer participation constraint for all types (10). Given that every participating consumer now purchases only once, firm profits are

$$\pi_e = \frac{c_e^i}{\overline{c}}(p - t) = \frac{\beta(u - p)(p - t)}{\overline{c}}. \tag{13}$$

Solving for the firm's optimal price we obtain

$$p_e = \frac{u + t}{2}. \tag{14}$$

Social welfare. We next derive social welfare with evaluations, SW_e. Every participating consumer generates social surplus u net of transaction cost t and sampling costs, and each consumer samples on average β^{-1} products to locate a match,

$$SW_e = \frac{c_e^i}{\overline{c}}(u-t) - \int_0^{c_e^i} \beta^{-1} c^i \; dc^i. \tag{15}$$

It is easy to show that social welfare is higher with evaluations as long as sampling costs in the population are low, that is $SW_e > SW_s$ if and only if $\overline{c} \leq 4$. In particular, firm profits are always higher with evaluations, $\pi_e > \pi_s$, but the impact of evaluations on consumer surplus is only positive as long as $\overline{c} \leq 2$.

Proposition 2 *Evaluations prior to purchase increase the concentration of sales in the market. Evaluations also reduce consumer search costs and avoid market break down. Firm profits, prices and consumer participation increase, but the effect on consumer surplus is only positive if sampling costs are low. Lowering sampling costs increases both firm profits and consumer surplus.*

Evaluations allow consumers to purchase only products they match with, and this increases the concentration of sales in the market. The increase is driven by the fact that product pools differ in their appeal to the consumer population. Therefore, when sales are realized by informed consumers, there is a market share shift from pools that appeal to a small share of the population to those that appeal to a larger share, benefitting mass market products the most.

Thus evaluations prior to purchase do not generate a long tail effect. Although evaluations have been proposed to reduce sales concentration by driving increased product exploration, our analysis suggests otherwise. The explanation is simple: consumer participation increases with evaluations, but consumers no longer purchase products they do not match with and this increases the concentration of sales. With independence of the concentration shift, however, evaluations can increase the sales volume of all products in the assortment. This case arises when the participation increase is very large, in particular when taste is fragmented (implying a low β) or transaction costs t are high.

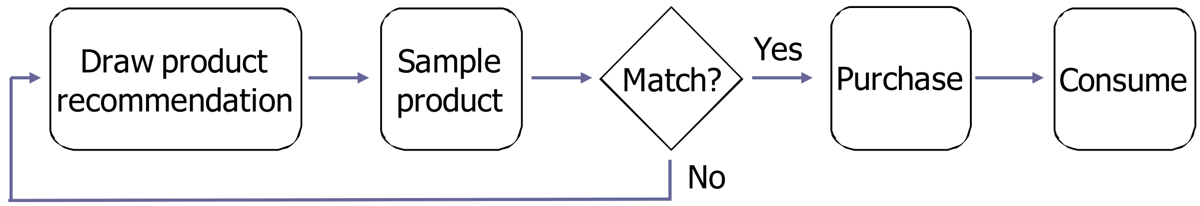
The impact of evaluations on the firm's demand is driven by two effects: (1) more consumers ready to participate at every price level, since evaluations reduce search costs by ensuring there are no unsuccessful purchases, and (2) every participating consumer now realizes a unique purchase once a match is located. These effects rotate the demand curve, expanding demand in the higher price range and contracting it in the lower range. As a result, the firm no longer discounts prices by β, as there are no unsuccessful purchases, and prices with evaluations are higher. Firm profits are strictly higher with evaluations, but consumer surplus only increases when sampling costs in the population are low. When sampling costs are high, evaluations allow the firm to appropriate a higher share of consumer surplus, and consumers are worse off.

Evaluations may be costly for the firm if additional resources or infrastructure are required. When transaction costs are high or taste is fragmented, $t < \beta u$, evaluations enable markets that would otherwise break down due to unsuccessful purchases. In these cases, the firm has strong incentives to implement evaluations. But the profitability of evaluations decreases quickly when taste becomes less fragmented, as $\beta \to 1$ and consumers incur few unsuccessful purchases without evaluations. Hence we should expect evaluations to be implemented when consumer taste is fragmented. The firm's incentives to implement evaluations also increase with match utility u and decrease with sampling costs $\bar{c}$, as higher sampling costs reduce market participation.

The above suggests that the firm has incentives to lower consumer's sampling costs. Casual evidence suggests that firms invest in doing so. Many bookstores, for example, provide a comfortable environment and cafeteria services for their customers to browse books. Online retailers invest in the infrastructure required to stream book excerpts, song clips and movie trailers to their customers. According to our model, this provides incentives for more consumers to search within the assortment, allowing the firm to sustain higher prices and increase profits.

4 Search with word of mouth

In this Section we introduce word of mouth by adding a third stage to the game. In the first stage, the monopolist chooses the price level in the market, p. Consumers willing to participate then choose between two available search strategies. In the second stage, as in the previous Section, consumers may search for a match with evaluations by sequentially drawing and sampling products from the assortment. In the third stage, consumers may search for a match by seeking recommendations from those that searched before them in the second stage. Instead of drawing products from the product space, consumers searching with recommendations draw product references from the mass of consumers that searched with evaluations. A consumer drawn to provide a recommendation identifies the product she matched with.[6] The consumer seeking recommendations may then draw and sample the identified product at cost c^i. The sequential search process when seeking recommendations is as follows:



Recommendations are drawn uniformly from the mass of consumers that searched with evaluations, which ensures that they are representative of the evaluating population's preferences. Each recommendation draw incurs a fixed cost r, since an additional step in the search is required to obtain information from others. To ensure that recommendations hold in the market, we need to assume $r < (u - t)/4$. Consumers providing recommendations freely identify their product match, and we will show that in doing so they benefit from lower prices.[7]

We also assume consumers form a correct expectation of the share of evaluating consumers of their type, s_e^t. In equilibrium, this determines their match probability with recommendations, as it captures how probable it is to obtain a recommendation from someone who shares their preferences. Past search experience, for example, can enable consumers to correctly forecast the value they derive from word of mouth.

Consumer search strategy. Consider the problem of an unmatched consumer in the third stage when the price level in the market is p. Product recommendations are drawn from the mass of consumers that searched with evaluations in the second stage. Note that that the sales distribution generated by evaluating consumers σ (12) carries over from our previous analysis, and describes the distribution of matches over product pools for the mass of evaluating consumers (although s_e^t will differ with word of mouth). The expected probability of a match for a consumer of type t seeking recommendations, denoted by α^t, is given by

[6] The recommendation exchange can be understood to take place either online or offline. In the first case, sampling consumers actively publish their recommendations and consumers seeking recommendations browse them. In the second case, consumers seeking recommendations observe which consumers have already matched and request product references from them.

[7] Since consumers seeking recommendations incur a sunk cost r on each draw, they would be willing to reward those that provide them instead. But assuming r is a sunk cost instead of a transfer allows us to ignore the bargaining problem that could arise between consumers. See Avery et al. [5] for a mechanism on the optimal provision of recommendations.

$$\alpha^t = \sigma_t + \sigma_N = \frac{1 + s_e^t}{2}. \tag{16}$$

The expression is a function of the share of evaluating consumers of type t. Thus the match probability when seeking recommendations will differ across types. As $\partial\alpha^t/\partial s_e^t > 0$, the larger the share of evaluating consumers of a consumer's own type, the larger her match probability when drawing a recommendation. We proceed by assuming that a positive mass of evaluating consumers of each type exists. Given that $s_e^t > 0$ and $N \geq 4$, it can be shown that $\alpha^t > \beta$ for all types.

The expected utility of seeking a new recommendation for consumer i of type t is

$$u_r^{t,i} = \alpha^t(u - p) - r - c^i, \tag{17}$$

as every recommendation draw incurs cost r in addition to sampling cost c^i. Note that the $u_r^{t,i}$ differs both across types due to α^t and within types depending on c^i. So while seeking recommendations yields a higher probability of a match on each draw, it is also more costly due to r. The utility of a successive draw, however, is constant throughout the search for any given consumer. Hence we can identify the consumer of type t which is strictly indifferent between seeking recommendations and not participating by equating $u_r^{t,i}$ to zero. We denote the indifferent recommendation seeker of type t by $c_r^{t,i}$, where

$$c_r^{t,i} = \alpha^t(u - p) - r. \tag{18}$$

Unmatched consumers of type t with a sampling cost $c^i \leq c_r^{t,i}$ choose to search with recommendations in the third stage, and those such that $c^{t,i} > c_r^{t,i}$ prefer to stay out of the market.

We next turn to the second stage of the game and analyze the decision to search with evaluations. As consumers anticipate that they may search with recommendations in the third stage, they decide which search strategy to pursue (if any) by comparing the expected utility of both. Given that the number of draws required for a match differs between both strategies, as $\alpha^t > \beta$ for all types, consumers need to evaluate the expected costs incurred to locate a match with both. Note that this comparison holds at any point of the search process for an unmatched consumer, as the expected utility of both search strategies is unaffected by past search history. This implies that no consumer that chooses to search with evaluations will abort the search in order to search with recommendations.

To identify the indifferent evaluator of type t, denoted by $c_e^{t,i}$, we equate the expected utility derived from both search strategies in order to locate a match, $u_r^{t,i} = u_e^i$. Note that u_e^i (9) carries over from our previous analysis and is type-independent. The expected number of draws required for a match with evaluations and recommendations are given by $1/\beta$ and $1/\alpha^t$ respectively. The indifferent evaluator of type t is then

$$\begin{aligned} u - p - \frac{r + c_e^{t,i}}{\alpha^t} &= u - p - \frac{c_e^{t,i}}{\beta} \\ c_e^{t,i} &= \frac{\beta r}{\alpha^t - \beta}. \end{aligned} \tag{19}$$

Consumers of type t with an evaluation cost $c^i \in [0, c_e^{t,i})$ prefer to search with evaluations in the second stage over seeking recommendations. For consistency, we require a positive mass of consumers of type t to seek recommendations in equilibrium, so $c_e^{t,i} < c_r^{t,i}$ must hold. As $c_r^{t,i}$ is decreasing in price level p for each type, we can identify the boundary price $\overline{p}^t$ by equating $c_e^{t,i} = c_r^{t,i}$,

$$\overline{p}^t = u - \frac{r}{\alpha^t - \beta}. \tag{20}$$

If no consumers of type t are willing to search with recommendations, consumers of this type will search only with evaluations and the indifferent evaluator of type t is given by $c_e^{t,i} = c_e^i$ as in (10), following our previous analysis. Note that participation is homogeneous across types that search only with evaluations.

We can now characterize consumer's search strategy. If $p < \overline{p}^t$, consumers of types t with sampling cost $c^i \in [0, c_e^{t,i})$ search with evaluations, and those with sampling cost $c^i \in [c_e^{t,i}, c_r^{t,i})$ seek recommendations. If $p \geq \overline{p}^t$, consumers of type t with sampling cost $c^i \in [0, c_e^i)$ search with evaluations. All remaining consumers stay out of the market.

We next characterize in more detail the composition of search strategies across types. Clearly, all types participate in the market, so there is always a positive mass of evaluators of each type. For those types that search with recommendations, note that $c_e^{t,i}$ is given by an implicit equation as α^t is a function of s_e^t, which in turn depends on the mass of evaluating consumers of all types, including the type considered. So the equilibrium participation of types that search with recommendations is defined by a system of implicit equations, one equation for each type. We next argue that the solution to this system satisfies that $c_e^{t,i}$ and s_e^t are decreasing and increasing in t, respectively, for types that search with recommendations. We show this by contradiction.

Assume recommendations hold for two types, t and $t+1$. First, consider the case $c_e^{t,i} = c_e^{t+1,i}$. This requires that $\alpha^t = \alpha^{t+1}$ by (19), which then implies that $s_e^t = s_e^{t+1}$ by (16). But on the other hand, since there is a larger share of consumers of type $t+1$ in the population, $s^t < s^{t+1}$ and $c_e^{t,i} = c_e^{t+1,i}$ both imply $s_e^t < s_e^{t+1}$, which is a contradiction. Next, consider the case $c_e^{t,i} < c_e^{t+1,i}$. This requires that $\alpha^t > \alpha^{t+1}$ by (19), which implies that $s_e^t > s_e^{t+1}$ by (16). But in this case $s^t < s^{t+1}$ and $c_e^{t,i} < c_e^{t+1,i}$ imply that $s_e^t < s_e^{t+1}$, which again is a contradiction. Hence the only feasible solution must satisfy $c_e^{t,i} > c_e^{t+1,i}$ and $s_e^t < s_e^{t+1}$ for types t and $t+1$.

We can now draw some conclusions for all types. Among the mass of consumers searching with evaluations and among the mass of consumers searching with recommendations, the shares of consumers of type t, denoted by s_e^t and s_r^t respectively, are increasing in t. To be sure, note that $c_e^{t,i}$ is constant across types that search with evaluations only, and that if type t searchers with recommendations but type $t-1$ does not, $s_e^{t-1} < s_e^t$ must hold. So, since s_e^t is increasing in t, then α^t must also be increasing in t. The latter implies that $c_r^{t,i}$ and $\overline{p}^t$ are increasing in t, so s_r^t must also be increasing in t. Thus, in equilibrium, types with a large population share (higher t) have more incentives to search with recommendations than types with a low population share (lower t), and if recommendations hold for type t in equilibrium they must also hold for types $j > t$.

Sales concentration. We next analyze the impact of word of mouth on sales concentration. Denote the sales distribution with word of mouth in the market by ρ, and let s_{er}^t be the share of consumers of type t among all participating consumers (with subindex er to denote that this includes both consumers searching with evaluations and recommendations). We argue that the introduction of word of mouth increases the concentration of sales, and show this in two steps. Consider the sales distribution in the market with evaluations only, σ (12). To analyze how ρ

differs from σ, we first account for the shift in consumer participation driven by word of mouth while keeping fixed the per-type sales distribution (the *participation effect*). In doing so, we derive a participation-adjusted sales distribution $\overline{\rho}$, where $\overline{\rho}_n = \sum_t s^t_{er}\sigma^t_n$. In the second step, we account for the change in the sales distribution generated by consumers seeking recommendations (the *mass market effect*) to obtain ρ, where $\rho_n = \sum_t s^t_{er}\rho^t_n$ and ρ^t is the sales distribution generated by consumers of type t in the market.

To account for the participation shift, we can directly write $\overline{\rho}$ using σ^t (11),

$$\overline{\rho}_n = \sum\nolimits_t s^t_{er}\sigma^t_n = \begin{cases} \frac{s^t_{er}}{2} & \text{if } n < N \\ \frac{1}{2} & \text{if } n = N \end{cases} . \tag{21}$$

To see how $\overline{\rho}$ differs from σ, denote the marginal type that searches with recommendations by t^r, such that types $t < t^r$ search only with evaluations and types $t \geq t^r$ search with both evaluations and recommendations. We have established that participation is homogeneous for types $t < t^r$ and given by c^i_e, while participation for types $t \geq t^r$ is given by $c^{t,i}_r$, where $c^{t,i}_r - c^{t,i}_e > 0$ and increasing in t. So s^t_{er} is constant for types $t < t^r$, and larger and increasing in t for types $t \geq t^r$. Inspection of $\overline{\rho}$ (21) and σ (12) reveals that this implies: (1) a market share transfer from product pools $n < t^r$ to pools $n \in (t^r, T)$, and (2) a market share transfer from pool n to pool $n+1$ within product pools $n \in (t^r, T)$. Since both transfers shift market share from low to high ranked product pools according to sales rank, the participation shift unambiguously increases concentration.

We next account for the shift in the per-type sales distribution generated by recommendation seekers. Note that ρ^t can be decomposed into sales driven by consumers of type t searching with evaluations, σ^t, and those searching with recommendations, which we denote by μ^t (which is only defined for consumer types that search with recommendations). To characterize the shift we next analyze how μ^t differs from σ^t.

To characterize μ^t, note that every recommendation draw is independent from past draws, so all consumers of type t seeking recommendations are identically and independently distributed. Thus μ^t is independent of the mass of consumers of type t seeking recommendations, and we need only characterize the distribution of matches for a single recommendation draw. The probability that a consumer of type t matches with product pool n when drawing a recommendation is given by

$\lambda_n^t \sigma_n$, and the probability of a match over all products is given by α^t. This implies

$$\mu_n^t = \frac{\sigma_n \lambda_n^t}{\alpha^t} = \begin{cases} \frac{s_e^t}{1+s_e^t} & \text{if } n = t \\ \frac{1}{1+s_e^t} & \text{if } n = N \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

Note that $\mu_t^t < 1/2$ and $\mu_N^t > 1/2$, so μ^t differs from σ^t in that $\mu_t^t < \sigma_t^t$ and $\mu_N^t > \sigma_N^t$. Since this implies a transfer from low to high ranked product pools according to sales rank, the sales distribution shift generated by recommendation seekers unambiguously increases concentration. Thus we conclude that word of mouth strictly increases the concentration of sales in the market.

Firm pricing. We next turn to the first stage of the game and analyze the firm's pricing problem. Given a price level p in the market, we have established that only types t such that $p < \overline{p}^t$ search with recommendations. So the number of consumer types that search with recommendations decreases (in a step-wise fashion) with prices, and if prices are sufficiently high, $p \geq \overline{p}^T$, no types search with recommendations. Let t^r be the marginal type seeking recommendations given p, such that $\overline{p}^{t^r-1} \leq p < \overline{p}^{t^r}$ (recall that $\overline{p}^t$ is increasing in t). Firm profits can be written as

$$\pi_r = [\sum\nolimits_{t=1}^{t_r-1} \frac{c_e^i}{\overline{c}} s^t + \sum\nolimits_{t=t_r}^{T} \frac{c_r^t}{\overline{c}} s^t](p - t). \tag{23}$$

The firm's demand curve is composed of $T + 1$ linear components, is continuous, (non-strictly) convex, and non-differentiable at $\overline{p}^t$ for $t \in (1, T)$. Each component of the demand curve describes a concave profit curve. Each profit curve lies above the rest in its own price range, and intersects with the curves of neighboring ranges at the price points $\overline{p}^t$ that separate components.

Define $\widehat{\alpha}^t$ as the following population-weighted match probability given the search strategies across of types when $t^r = t$,

$$\widehat{\alpha}^t = \frac{\sum_{t=t_r}^{T} s^t}{\sum_{t=1}^{t_r-1} s^t \beta + \sum_{t=t_r}^{T} s^t \alpha^t}, \tag{24}$$

where $\widehat{\alpha}^t > 0$. For each component of demand such that $t_r \in (1, T)$ we can derive the maximum of the corresponding profit curve from (23), denoted by $\widehat{p}^t$, where

$$\widehat{p}^t = \frac{u + t - r\widehat{\alpha}^t}{2}. \tag{25}$$

For the component in which $t_r = T + 1$, consumers search only with evaluations and $\widehat{p}^{T+1} = p_e$ as in (14).

To identify the profit maximizing solution p_r, the firm need only evaluate profits at well defined maximums. Given the component-linearity and convexity of the demand curve, it follows that $\widehat{p}^t$ is increasing in t (so $\widehat{\alpha}^t$ must be decreasing in t). Well defined maximums are those such that $\overline{p}^{t-1} \leq \widehat{p}^t < \overline{p}^t$. In addition, whenever multiple maximums are well defined, it follows that they pertain to contiguous ranges. Our restriction on r ensures that the firm's solution falls in the range $p_r < p^T$ and recommendations hold in equilibrium for some consumer types.[8]

Social welfare. With respect to the solution with no word of mouth derived in Section 3.1, whenever recommendations hold in equilibrium for some consumer types we have established that: (1) consumer participation is higher, and (2) prices are lower. This implies that word of mouth strictly increases firm profits and consumers surplus, unambiguously increasing social welfare.

Proposition 3 *Word of mouth increases the concentration of sales in the market. Word of mouth also reduces consumer search costs, benefits consumers with widespread preferences the most, and increases in value with the fragmentation of taste. Firm profits and consumer surplus increase with higher consumer participation and lower product prices. Lowering the cost of recommendations intensifies the previous effects.*

Word of mouth arises endogenously, and the exchange of product information between consumers reduces search costs in the market. Word of mouth allows consumers to benefit from those that searched before them, increasing the probability of a match by gathering information about which products to sample. The value of word of mouth increases with the fragmentation of taste. The higher the fragmentation, the lower the match probability when sampling products from the assortment. This renders the match probability with recommendations more attractive, in particular

[8] This requires that the maximum for the component without word of mouth is not well defined, $\widehat{p}^{T+1} < \overline{p}^T$, which implies $r < \frac{1}{2}(u-t)(\alpha^T - \beta)$. Given that in equilibrium $\alpha^T > (1 + 1/T)/2$ and $\beta = 2/(T+1)$, it follows that $\alpha^T - \beta$ is increasing in T and $Lim_{T\to\infty}\ \alpha^T - \beta = 1/2$. So $r < (u-t)/4$ is sufficient to ensure word of mouth holds in equilibrium.

given the high probability of identifying a mass market product.

Consumers with low sampling costs prefer to search with evaluations, as recommendations are costly, while those with high sampling costs are better off searching with recommendations. Consumers seeking recommendations, however, cannot observe the preferences of those providing them, so recommendations end up being exchanged in the market between consumers with different product preferences. This cross-type exchange has an asymmetric impact across consumer types and across product pools. We decompose the impact in two effects, a *mass market effect* and a *participation effect*.

The mass market effect follows from the fact that all consumers agree on mass market products. Consumers seeking recommendations are more likely to match with mass market products than those searching with evaluations, as successful cross-type recommendation can only yield a match with these products. This effect increases the market share of mass market products.

The participation effect is driven by the fact that some product preferences are more widespread in the consumer population. In equilibrium, more recommendations originate from consumers with widespread preferences, as a larger mass of these consumers choose to search with evaluations. Thus the benefit consumers derive from word of mouth increases with the prevalence of their taste in the population. As a result, consumers with widespread preferences exhibit higher participation, and a higher share of them search with recommendations. On the other hand, word of mouth may not pay off for consumers with uncommon preferences if their share in the population is sufficiently low, and those consumers may search only with evaluations. This effect increases the market shares of product pools with widespread appeal and decreases that of pools with low appeal.

Both the mass market and the participation effect increase the concentration of sales, and the shift in concentration grows with the share of consumers searching with recommendations. Hence word of mouth does not generate a long tail effect. On the contrary, products enjoy increasing returns to appealing to a larger share of the consumer population, reinforcing their market shares. As a result, market shares overestimate the appeal of best-selling products and underestimate that of lesser performing products. The result is reminiscent of the double jeopardy effect discussed by Ehrenberg et al. [11], where small brands perform comparatively worse than large brands. Our model suggests that word of mouth could be an explanatory factor for such effects.

The result is robust. We have considered positive recommendations only, as negative recommendations have no value in the market. For a consumer, following a negative recommendation and discarding a single product from the assortment does not increase the probability of locating a match. The result carries over to discrete product spaces, where it can be shown that the informational value of negative recommendations quickly decreases with the size of the assortment. Presumably for this reason, we do not observe consumers seeking recommendations on what to dislike within large assortments.

We have assumed recommendations enjoy no salience, as consumers do not place additional value on a match that results from a recommendation. Senecal and Nantel [18] report a series of experiments that suggest recommendations have an influential effect on consumers beyond awareness. In our framework, salient recommendations would increase the expected utility consumers derive from recommendations $u_r^{t,i}$, increasing consumer participation and the share of consumers searching with recommendations. Hence salience would reinforce the increase in concentration.

Our model is also static. If we considered a dynamic model of consumer arrival where recommendations originated, at any point in time, from all consumers that arrived earlier (not only those that searched with evaluations) sales concentration would only increase. In this scenario, recommendations originating from consumers that previously matched seeking recommendations themselves would further reinforce the mass market and participation effects. Such a dynamic model could approximate the findings on popularity feedback reported by Salganik et al. [17] and Tucker and Zhang [19].

For the firm, word of mouth expands demand in the low price range. Word of mouth does not hold in the high price range, as consumers seeking recommendations are those with high sampling costs and their willingness to participate is lower than that of consumers searching with evaluations. As a result, the firm discounts prices to account for the value of recommendations in the market and word of mouth holds in equilibrium. The share of participating consumers that seek recommendations increases with consumption utility u and the fragmentation of taste T, and decreases with recommendation cost r. With respect to the market with no word of mouth, equilibrium prices are lower and participation is higher. Social welfare is unambiguously higher, as both firm profits and consumer surplus increase. All consumers, including those searching with evaluations, benefit from word of mouth.

Similarly to lowering sampling costs for consumers, facilitating the exchange of recommendations by lowering their cost has the potential to expand markets. This provides incentives for the firm to play an active role in the process, an opportunity fueled by the online environment. Online retailers such as Amazon have designed platforms to facilitate the exchange of product recommendations, becoming valuable resources for consumers. Chevalier and Mayzlin [9] analyze the impact of online book reviews at two major online retailers. They find that most reviews are overwhelmingly positive and increase the relative sales at the retailer they are posted on. The findings are consistent with our model, and suggest that part of the market growth spurred by electronic commerce may be attributable to word of mouth alone.

4.1 Taste matching

Our analysis has shown that word of mouth arises endogenously and creates value in the market, but has also revealed the existence of inefficient recommendation exchanges between consumers with different preferences. Consumers stand to benefit from matching with others of their same type in the word of mouth exchange, as this would increase their match probability with recommendations, and we have argued that the Internet has significantly increased their ability to do so. To this end, we next analyze the impact of taste matching on the market. We build on the same setup and timing as in the previous Section, but introduce an exogenous mechanism that allows consumers seeking recommendations to obtain them from those that share their product preferences.

Consumer search strategy. With taste matching, recommendations always yield a match since they are exchanged only between consumers of the same type. Therefore $\alpha^t = 1$ for all t, and the match probability with recommendations no longer depends on the composition of types among evaluating consumers. Note that we require a positive mass of evaluating consumers of each type to provide recommendations in the market, and we proceed by assuming this is the case.

The impact of taste matching on the market follows from our analysis in the previous Section taking into account that $\alpha^t = 1$. This homogenizes across types the utility of recommendations $u_r^{t,i}$(17), the indifferent recommendation seeker $c_r^{t,i}$ (18), the indifferent evaluator $c_e^{t,i}$ (19), and the boundary recommendation price $\overline{p}^t$. To account for the fact that they no longer depend on t, we denote them by u_r^i, c_r^i, c_e^i, and $\overline{p}$ respectively.

If prices are above the boundary recommendation price, $p \geq \overline{p}$, all types search only with evaluations and the market configuration is equivalent to that of Section 3.1. If $p < \overline{p}$, all types search with recommendations. In this case $0 < c_e^i < c_r^i$ holds for all types, and there is a positive mass of consumers of each type willing to search with evaluations. This also implies that $s_e^t = s_r^t = s_{er}^t = s^t$, and participation is homogeneous across types.

Sales concentration. We next argue that the introduction of taste matching reduces sales concentration. Consider the participation shift, given by $\overline{\rho}$ in (21). Since $s_{er}^t = s_e^t$ with taste matching, $\overline{\rho} = \sigma$ and the participation shift does not alter concentration with respect to evaluations. Next, consider the sales distribution shift generated by recommendation seekers. With taste matching, consumers only draw recommendations from evaluating consumers of their own type, so μ^t is now given by

$$\mu_n^t = \frac{\sigma_n^t \lambda_n^t}{\alpha^t} = \sigma_n^t. \tag{26}$$

This implies that $\rho^t = \sigma^t$, and recommendation seekers do not alter concentration with respect to evaluations. We conclude that $\rho = \sigma$ and sales concentration with taste matching is equivalent to that derived in Section 3.1 with evaluations only.

Firm pricing. The firm's profit function π_r (23) carries over by taking into account that there is now a unique non-differentiability at $\overline{p}$. The demand curve has two linear components; either $p \geq \overline{p}$ and $t^r = T + 1$, or $p < \overline{p}$ and $t^r = 1$. The maximum of the profit curve in the range $p < \overline{p}$ is given by

$$p_{tm} = \frac{u + t - r}{2}, \tag{27}$$

since $\widehat{\alpha}^1 = 1$ given that $\alpha^t = 1$ for all types (we need only consider the case $t^r = 1$ in the range $p < \overline{p}$). The firm's profit maximizing price is p_{tm}, given that our restriction on r ensures that $p_{tm} < \overline{p}$.[9]

[9] The maximum of the profit curve in the range $p \geq \overline{p}$ is given by p_e in (14). For the solution to be in the range $p < \overline{p}$ we require that $p_e < \overline{p}$, which implies $r < \frac{1}{2}(u-t)(1-\beta)$. This always holds given our assumption $r < (u-t)/4$. In addition, this equilibrium marks the highest consumer participation predicted in the model. For the market to remain uncovered in equilibrium, we require $c_r^i < \overline{c}$, which given p_{tm} implies $\overline{c} > \frac{1}{2}(u - t - r)$. This lower boundary on $\overline{c}$ ensures the market is uncovered in all equilibria derived in our analysis.

Social welfare. With respect to word of mouth in the previous Section, consumer participation increases in the price range $p < \overline{p}$, unambiguously increasing firm profits in equilibrium.

The impact of taste matching on consumer surplus is extremely complex to characterize, unfortunately. Taste matching reduces search costs for consumers, but in addition may increase or decrease prices, rendering the net effect on consumer surplus ambiguous. To illustrate this, consider consumer surplus in the market when taking α and β as exogenous,

$$CW_{tm} = \frac{c_r^i}{\overline{c}} u - \int_0^{c_e^i} \beta^{-1} c^i \; dc^i - \int_{c_e^i}^{c_r^i} \alpha^{-1} (c^i + r) \; dc^i. \tag{28}$$

In this scenario, prices are increasing in α, and it can be shown that $\partial CW_{tm}/\partial\alpha < 0$ if sampling costs $\overline{c}$ are sufficiently high.

The impact on consumer surplus in our model is more complex, as α and β differ across types in the word of mouth equilibrium, and the sign and intensity of the price change depends on $\widehat{\alpha}^t$ (24) in word of mouth prices p_r. Thus $p_{tm} < p_r$ and $p_{tm} > p_r$ are possible. Due to the complexity of $\widehat{\alpha}^t$ we are unable to pin down the exact behavior of prices in order to draw clear-cut conclusions, but the above suggests that consumer surplus will increase whenever $\widehat{\alpha}^t$ or sampling costs $\overline{c}$ are low.

Proposition 4 *Taste matching generates a long tail effect, reducing the concentration of sales in the market. Taste matching also reduces search costs, increasing the value of recommendations for all consumers and benefiting those with uncommon preferences the most. Firm profits increase due to higher consumer participation, but the impact on prices and consumer surplus is ambiguous.*

Taste matching ensures recommendations are exchanged only between consumers that share the same product preferences. This implies that recommendations always yield a product match, becoming more valuable for consumers and reducing search costs in the market. In fact, the value consumers derive from recommendations no longer depends on how prevalent their preferences are in the population, so consumers with widespread preferences no longer enjoy an advantage over their peers. Thus consumers with uncommon preferences benefit the most from taste matching, and since there is no longer an asymmetric benefit across the consumer population, participation becomes homogeneous across types.

By eliminating the cross-type exchange of recommendations, taste matching generates a long tail effect and reduces the concentration of sales in the market. To see this, consider the effects driving concentration with word of mouth. On the one hand, there is no longer a mass market effect. As there are no cross-type recommendations, consumers seeking recommendations no longer have a higher probability of matching with mass market products than matching with the remaining of their preferred products. This shifts market share from mass market products to all other product pools with respect to word of mouth. On the other hand, there is no longer a participation effect. Again, since there are no cross-type recommendations, consumers with widespread preferences no longer derive higher value from recommendations than others and do not participate comparatively more in the market. This shifts market share from products that appeal to a large share of the population to those that appeal to a lower share. As a result, taste matching reverses the increase in concentration driven by word of mouth, and sales concentration is now equivalent to that derived in Section 3.1 with evaluations only.

Taste matching expands the firm's demand in the low price range. More consumers are now ready to participate by seeking recommendations in the market, and to do so with higher prices. The firm adjusts prices to account for the higher value of recommendations in the market, and this may increase or decrease prices. The sign and intensity of the change depends on the exact market configuration with word of mouth. Firm profits increase due to higher demand, but the impact on consumer surplus is ambiguous. Consumers searching with recommendations benefit from lower search costs, but a price increase could offset this benefit. Inspection of prices in the word of mouth equilibrium and our analysis above suggest that consumer surplus increases when taste fragmentation T and sampling costs $\bar{c}$ are low, and the cost of recommendations r is high. To be sure, consumer surplus is strictly higher than with evaluations only. Also note that, independently of the aggregate impact on consumer surplus, individual consumers always benefit from taste matching when seeking recommendations.

Our model shows that consumers and the firm have strong incentives to use and deploy mechanisms that facilitate taste matching in the market. Several such mechanisms have emerged on the Internet, facilitated by cumulative innovations and its decentralized architecture. Consumers can use search engines to locate community sites that share their interests, browse the collections of akin users on peer-to-peer networks, and interact with fan communities on social networks. More recently, online retailers and content providers have become major players in this area by heavily investing to deploy and develop recommender systems. These systems mostly rely on collaborative filtering techniques, generating recommendations by identifying taste similarity in consumer preference data, and essentially automating the taste matching process.[10] Our model explains how these systems create value in the market. Indeed, if firms offering better recommendations can capture a share of the value they generate, recommenders can sustain a competitive advantage. We next discuss the strategic implications of our findings for the firm.

In real world applications, recommender systems exhibit a learning curve to identify a consumer's preferences. Due to this, consumers generally face switching costs to obtain recommendations from competing systems. Recommender systems also exhibit network effects due to the information sparsity problem; the larger the database on consumer preferences, the more accurate the recommendations generated. Both factors suggest the firm can benefit from rewarding consumers to join the system, growing its userbase and benefitting from a lock-in phenomenon. And since our model shows that consumers with uncommon preferences derive higher utility from the system, they also exhibit higher willingness to pay for its recommendations.

Recommender systems reduce consumer's incentives to evaluate products. Our model predicts that the mass of consumers searching with evaluations decreases in presence of the recommender. Due to the information sparsity problem, rewarding evaluating consumers for the information they provide may become an important strategic consideration. This problem has been considered by Avery et al. [5]. From a mechanism design perspective, our search model with heterogeneous preferences contributes two insights. First, information on product matches, rather than on products that failed to yield a match, is more valuable for large assortments and should command a higher reward. Second, due to their lower presence in the population and the value generated from their input, product evaluations from consumers with uncommon preferences should also command a higher reward.

Finally, the potential of recommender systems to reduce the concentration of sales drives other

[10] A taxonomy of recommender systems and an overview of the related computer science literature are presented by Adomavicius and Tuzhilin [2]. For a brief discussion on the economics of recommender systems, see Resnick and Varian [15].

strategic considerations. In particular, if firms differ in their inventory costs, the long tail effect will benefit those firms with low costs, capable of increasing the depth of their assortment beyond that of competitors and catering to niche consumers and products. It is unsurprising then that online retail and the advent of digital distribution, characterized by such a competitive advantage, have fostered the development and widespread deployment of recommender systems.[11]

5 Concluding remarks

We have provided a theoretical framework to understand the impact of consumer search on the concentration of sales and its implications for the firm. In doing so, our model contributes a foundation to understand the value of product recommendations in markets characterized by large assortments of horizontally differentiated products. We have analyzed the impact of product evaluations and word of mouth, and shown that they reduce consumer search costs and increase the concentration of sales. This can explain their prevalence in the markets considered, such as music, cinema, literature or video game entertainment, also characterized by high concentration. Therefore, consumers with uncommon preferences in the population and the products that appeal to them are underserved in the market.

Building on these results, we have analyzed the impact of mechanisms that improve taste matching in the word of mouth exchange. Such mechanisms have become commonplace with recent developments in telecommunications and information technologies, and allow consumers seeking product recommendations to obtain them from others that share their taste. We have shown that matching reduces search costs by improving the efficiency of the information exchange between consumers, and also reduces the concentration of sales. This result contributes to the long tail debate, as matching is arguably playing an important role in the markets where the long tail has been reported. It is also a first step to understand the mechanisms that can reduce sales concentration, since other mechanisms previously considered in the literature such as advertising and product popularity information have been shown to increase it.

[11] Consider for example the case of Netflix and Blockbuster. It has been reported that Netflix's recommender system drives 60 percent of its movie rentals, most of them titles not readily available in traditional video stores. See 'The screens issue. If you liked this, you're sure to love that,' The New York Times, November 23, 2008.

A prominent case of taste matching can be found in the recommender systems implemented by major online retailers on their storefronts. Our framework provides a rationale for the presence of an unbiased recommender, and the firm's incentives to reduce search costs in the market may outweigh strategic opportunities for the manipulation of product recommendations. Accounting for consumer trust and supply side competition would only intensify the case. Amazon, for example, allows third-party sellers to supply the products indexed by its recommender system, limiting its ability to profitably manipulate recommendations.

While the long tail debate has focused on the concentration of sales, we have shown that a long tail effect such as that driven by taste matching increases the sales volume of products that appeal to smaller shares of the consumer population. Higher demand for these products can increase product variety in the long term. In artistic markets, such an effect provides incentives for emerging artists and those that appeal to smaller audiences to participate in the market. Lower sales concentration may only be one of the shorter term implications of improved taste matching in markets.

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