How Does Popularity Information Affect Choices? Theory and A Field Experiment

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Abstract

Does popularity information (i.e., information on the frequency with which a product has been chosen) benefit niche or mainstream products more? Popularity information is commonly believed to reinforce existing trends, as customers flock to popular mainstream products. We develop a theoretical model which predicts that popularity information may in fact benefit niche products disproportionately. We empirically examine this prediction using field experiment data from a website that lists wedding service vendors. We find that the marginal benefit of popularity information is indeed higher for niche vendors than for mainstream vendors. This result is further supported in a lab experiment. The findings help explain the persistence of the “long tail” despite the widespread firm practice of highlighting their bestsellers.

Keywords: Popularity Information, Learning, Quality Inference, Decisions Under Uncertainty, Strategic Information Release, Category Management, Segmentation, Niche Marketing, Long Tail, Internet Marketing
1 Introduction

It is becoming more common for businesses to publicize the popularity of their products. Barnes & Noble promotes its bestsellers; Blockbuster deliberately highlights popular movie titles; 60 of the top 100 U.S. websites display information about what products previous customers chose.

Previous academic work suggests that popularity information reinforces existing popularity patterns by diverting customers to already popular products and driving unpopular products into further obscurity. Salganik, Dodds, and Watts (2006) find that experiment participants in an artificial music market respond positively to popularity information about previous music downloads. Duflo, Kremer, and Robinson (2006) find that the low adoption of a profitable fertilizer in western Kenya hinders further adoption. However, if popularity information drives choice in a wholly winner-takes-all way, that fails to explain the prosperity of low-volume products. Indeed, empirical studies have documented overwhelming evidence of a “long tail” effect in e-commerce, where customers buy many different kinds of less popular items online despite the availability of popularity information (e.g., Brynjolfsson, Hu, and Smith (2003), Anderson (2006), Brynjolfsson, Hu, and Simester (2007), and Oberholzer-Gee and Elberse (2007)).

We show that, contrary to the winner-takes-all implication of existing social learning models, niche products may benefit more from popularity information than mainstream products. In this study, a mainstream (niche) product refers to a product that, due to horizontal match, offers high (low) utility for the majority of customers. For example, consider two stores, one downtown (mainstream) and the other in a rural area (niche). Information that a store is popular will convey a positive quality signal to customers, but the strength of this signal differs for the two stores. Customers may attribute part of the downtown store’s popularity to its naturally larger customer base. They may believe, however, that the rural store has “something special” that justifies its popularity despite its naturally smaller customer base.

We formalize this intuition within a theoretical framework that integrates customers’ hor-
orizontal match into the existing model of observational learning. We define popularity as the frequency with which a product has been chosen. We consider two horizontally differentiated products, one mainstream product that appeals most to the majority of customers, and other a niche product that appeals most to a minority of customers. We then distinguish between two sources of popularity: vertical quality and horizontal match with the customer. An item may be unpopular either because quality is perceived to be low or because it serves a niche segment with a slim chance of match. The vertical quality implication of popularity is therefore moderated by horizontal match, following Bayes’ rule.¹

We empirically evaluate this pro-niche theory against the “winner-takes-all” or “superstar” pro-mainstream theory, using field experimental data from a website that lists wedding services vendors. This website experimented with shifting from a traditional, yellow pages style of alphabetical listing, where no popularity information was displayed, to a more contemporary style where popularity information was displayed and listings were ranked by popularity. The website measured vendor popularity by how many times customers clicked on its URL. We first compare the distribution of clicks in this new format with the original format, and find that the release of popularity information (in combination with ranking by popularity information to make this information salient) increases overall interest in the category. We then investigate which vendors benefit the most from popularity information. To do so, we classify vendors as mainstream or niche based on how many people live near them (a vendor’s location is the only salient horizontal differentiator displayed on the website.) We find that vendors in rural locations benefit more from their popularity than vendors in urban locations. We verify the robustness of these results using both a regression-discontinuity approach and instrumental variables. We also repeat the experiment in the lab with a purely between-subjects design. Again, we find that the release of popularity information benefits a relatively popular niche product most.

¹Also using Bayes’ rule as a key element of inference, Mayzlin (2006) derives the unconventional result that firms allocate more resources to promoting inferior products.
These findings are encouraging to multi-product marketers, category managers, and internet platforms who are interested in increasing total category traffic. First, the results confirm that popularity information can serve as a powerful marketing tool to facilitate category growth. Second, the results suggest ways to use popularity information as an effective marketing tool. Specifically, a category can receive greater marginal benefits from highlighting the popularity of a niche vendor than an equally popular mainstream vendor.

This paper draws on and contributes to two lines of research. The first is research on observational learning. Classic analytical models of observational learning show how consumers use previous choices to make inferences about the vertical quality of products (Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992)). Empirical studies in this direction have also focused on documenting evidences of vertical quality inference, either in the lab (e.g. Anderson and Holt (1997), Çelen and Kariv (2004) or in the field (Zhang 2007)). All these studies arrive at the same conclusion that popularity information benefits high-volume items. However, by introducing horizontal differentiation into the inference process we are able to provide novel results that contrast with this previous literature. In particular, we find that the highest volume products do not necessarily benefit more than lower volume products from informational cascades. Additionally, the use of broad-scale field experiment data in this study bypasses the identification issues that have challenged previous work.

This paper also adds to the long tail literature, such as Brynjolfsson, Hu, and Smith (2003), Anderson (2006), Brynjolfsson, Hu, and Simester (2007), and Oberholzer-Gee and Elberse (2007) by explaining how researchers have separately discovered the superstar effect (Rosen (1981)) and the long tail effect. We do this by studying how the release of popularity information affects customer interest in low-demand products that the long tail is meant to include. We find that if the long tail is composed of niche products, rather than merely unpopular mainstream products,

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2Quality inference may be observationally equivalent to situations where customers receive utility from conformity. This secondary mechanism is not relevant, however, to our empirical setting, because individual choices are rarely subject to social pressure to conform, and network externalities are minimal.

3
popularity information can further strengthen the long tail. This finding allows us to understand exactly how niche products survive despite the widespread publicizing of popularity information, which has been conventionally believed to hurt less popular products.

The paper is organized as follows. Section 2 develops an analytical model to illustrate how popularity information can benefit niche products more than mainstream products. Section 3 discusses the field experimental design and implementation. Section 4 presents the field experimental data and estimation results. Section 5 describes further robustness checks through a lab experiment. Section 6 concludes the paper and discusses directions for future research.

2 A Model of How Popularity Information Affects Choices

This section illustrates how product popularity information redistributes customer choices through an observational learning mechanism. Products are allowed to be both horizontally and vertically differentiated, where horizontal product attributes are observed by all customers but vertical quality is unobservable. We define a mainstream (niche) product as a product that, solely due to horizontal match, brings higher (lower) utility to the majority of customers. We then define product popularity as the frequency with which the product is chosen by a set of customers. In other words, popularity can be driven by both quality and match, and a niche product can be popular if its quality is believed to be superior. Each customer possesses a piece of private information about the vertical quality, and her product choice reflects that information. Therefore, product popularity information can be used by subsequent customers to update their knowledge of the vertical quality. Since popularity is driven by both horizontal match and vertical quality, the same degree of popularity conveys a stronger (weaker) quality signal if the product serves a niche (mainstream) customer segment. To see this, consider two stores, one downtown and the

\[\text{In this model, customers draw quality inferences from others’ actual product choices. In comparison, Alison K.C. Lo and Staelin (2007) explore quality inferences from what products are offered to other customers. They find in the lab that a customer will infer high quality if a product is associated with a promotion that is a misfit to herself but a fit to another group of expert customers.}\]
other in a rural area. Information that a store is popular will convey a positive quality signal to customers, but the strength of this signal is different for the two stores. If a hypothetical customer saw an identical number of customers in each store, they might draw different quality inferences. For the downtown store, customers may attribute part of its popularity to its naturally larger customer base. For the rural store, they may believe it has “something special” that justifies its popularity despite its naturally smaller customer base. Crucially, each product’s popularity is judged relative to customer’s expectations about its customer base. Therefore, popularity information may benefit a niche product more than an equally popular mainstream product.

2.1 Model Setup

Suppose there are two vendors within the same category, each carrying one product. Customers are heterogenous in their product tastes and are divided into two types with fraction $\theta$ and $1 - \theta$ respectively. Assume $1/2 < \theta < 1$ such that one vendor produces a “mainstream” (denoted as $M$ throughout the analysis) product and the other vendor supplies a “niche” (denoted as $N$) product. This means that niche and mainstream products are defined relative to the size of their expected customer bases. A customer derives utility $t \geq 0$ by choosing the vendor that suits her taste, and utility 0 otherwise, where $t$ can be interpreted as the degree of taste heterogeneity. Each customer knows her own taste but does not observe other customers’ tastes. The values of $\theta$ and $t$ are common knowledge.

The vertical quality of the two products, denoted as $v_M$ and $v_N$ respectively, can be either 0 or 1 with equal prior probability. Customers are uncertain about which value the vertical quality takes. However, each customer receives a private quality signal which can be either high ($H$) or low ($L$). These private signals are identically and, conditional on the true quality, independently distributed. Suppose the conditional signal probabilities are $p(H|v_j = 1) = p(L|v_j = 0) = q$, where $j \in \{M, N\}$. Assume $1/2 < q < 1$ so that private signals are informative yet imperfect.
Each customer incurs cost $c$ in visiting a vendor. We treat $c$ as exogenously given in the analyses.\footnote{In the field experiment context of this study, $c$ can be a web viewer’s costs of clicking on each vendor. In the lab experiment context, $c$ is the product price which is fixed by design.} Let $I(\cdot)$ denote the indicator variable which equals 1 if the argument inside is true and 0 otherwise. Let $U_{ij}$ denote the net utility for a customer of taste $i \in \{M, N\}$ to visit vendor $j$:

$$U_{ij} = v_j + t \cdot I(i = j) - c$$  \hspace{1cm} (1)

Customers are allowed to visit multiple vendors.\footnote{The assumption that customers can visit multiple vendors is consistent with the experimental settings of this study. Nevertheless, the qualitative conclusions of the analysis remain valid when customers are restricted to visit a single vendor. Mathematical proof is available upon request.} A customer of type $i$ will visit vendor $j$ if and only if $E(U_{ij}) \geq 0$, where

$$E(U_{ij}) = 1 \cdot p(v_j = 1) + t \cdot I(i = j) - c$$ \hspace{1cm} (2)

### 2.2 Choices without Popularity Information

Knowing her own taste, the horizontal type of the products, and the cost of visiting each vendor, a customer determines whether to visit a vendor based on her expected vertical quality of the product. In the absence of popularity information, each customer infers the vertical quality using her private signal. By Bayes’ rule, the posterior belief about $v_j$ after observing an $H$ signal on product $j$ is

$$p(v_j = 1|H) = \frac{p(H|v_j = 1)p(v_j = 1)}{p(H|v_j = 1)p(v_j = 1) + p(H|v_j = 0)p(v_j = 0)} = \frac{q/2}{q/2 + (1-q)/2} = q$$

Therefore, the expected vertical quality of product $j$ upon receiving an $H$ signal is $E(v_j|H) = q$. Similarly, the expected vertical quality upon receiving an $L$ signal is $E(v_j|L) = 1 - q$. It follows from Equation 1 that the expected utility a type $i$ customer receives from visiting vendor $j$ upon
receiving an $H$ signal is

$$E(U_{ij}|H) = q + t \cdot I(i = j) - c$$

(3)

Similarly, the expected utility for type $i$ to visit vendor $j$ upon receiving an $L$ signal is

$$E(U_{ij}|L) = 1 - q + t \cdot I(i = j) - c$$

(4)

Note that if the cost of visiting a vendor is low enough (i.e., $c < \bar{c} = 1 - q$), a customer will visit both vendors regardless of taste match and her private signal. Meanwhile, if $c$ is high enough (i.e., $c > \bar{c} = q + t$), a customer will visit neither vendor. In either case, a customer’s decision reveals no information to subsequent customers about her private signal. Releasing popularity information therefore would not affect subsequent choices. For the rest of the analyses we focus on the nondegenerate case where $c \in [\underline{c}, \bar{c}]$.

When this cost condition holds, a customer will always visit a matching vendor upon an $H$ signal, and will never visit a mismatching vendor upon an $L$ signal. In between, a customer will visit a matching vendor despite an $L$ signal if $c \leq c_M = 1 - q + t$, where $c_M$ denotes the cost threshold below which match dictates visit regardless of the private signal. Note that $c_M$ decreases with $q$ and increases with $t$. In other words, match is a sufficient condition of choice when taste heterogeneity is high and signal precision is low. Similarly, a customer will visit a vendor upon an $H$ signal despite mismatch if $c \leq c_S = q$, where $c_S$ denotes the cost threshold below which an $H$ signal alone guarantees visit, which is more likely to happen when private signals are more indicative of the underlying vertical quality.

Figure 1 summarizes customer choices in the absence of popularity information. When $c$ is sufficiently low (i.e., $c < \min(c_S, c_M)$), a customer decides not to visit a vendor if and only if it is a mismatching type and the signal is $L$. On the other hand, when $c$ is sufficiently high (i.e., $c > \max(c_S, c_M)$), a customer visits a vendor if and only if it is the matching type and the
signal is \( H \). More interestingly, the sufficient and necessary condition of visit is a match when \( c_S < c < c_M \), and is an \( H \) signal when \( c_M < c < c_S \). Note that \( c_S < c_M \) if and only if \( 1 + t > 2q \).

The intuition is that horizontal match (vertical quality) is more likely to determine choices when customer tastes are heterogeneous (homogeneous) and private signals noisy (accurate).

### 2.3 Choices with Popularity Information

Consider a sequence of two customers.\(^6\) The first customer has made her choice independently as modeled in the previous section. There are four possible choices, where the first customer visits either vendor, both, or neither. How information on the first customer’s choice influences the second customer depends on the value of \( c, t, \) and \( q \), which we discuss below.

When \( c \in (c_S, c_M) \), which requires \( 1 + t > 2q \), the first customer’s choice is solely determined

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\(^6\)The model can be extended to a general case where popularity information consists of independent choices of \( n \) customers. The results remain valid. Please see the Appendix.
by match and therefore reveals nothing about her private signal (see the upper half of Figure 1). Recall that a customer’s prior vertical quality perception before receiving her private signal is $E(v_j) = 1/2, j \in \{M, N\}$. Let 1 represent the event that the first customer has chosen to visit the vendor and 0 otherwise. Information on the first customer’s choice does not change the second customer’s prior quality perception:

$$E(v_j|1) = E(v_j|\text{match}) = E(v_j) = 1/2$$
$$E(v_j|0) = E(v_j|\text{mismatch}) = E(v_j) = 1/2, \quad j \in \{M, N\}$$

(5)

Releasing popularity information in this scenario therefore does not change subsequent visits.

**Proposition 1.** When customer tastes are sufficiently heterogeneous and quality signals sufficiently noisy $(1 + t > 2q)$, releasing popularity information may not change subsequent choices.

When $c \in (c_M, c_S)$, which requires $1 + t < 2q$, the first customer’s choice is solely determined by her private signal and therefore contains the most information relevant to the second customer (see the lower half of Figure 1). The second customer updates her quality perception of a vendor upwards (downwards) if the vendor has (not) received a visit:

$$E(v_j|1) = E(v_j|H) = q > 1/2$$
$$E(v_j|0) = E(v_j|L) = 1 - q < 1/2, \quad j \in \{M, N\}$$

(6)

As a result, releasing popularity information generates a bandwagon or superstar effect where, other things being equal, a visit increases the chance of more customer interest.

**Proposition 2.** When customer tastes are sufficiently homogenous and quality signals sufficiently accurate $(1 + t < 2q)$, releasing popularity information may generate bandwagon effects that benefit (hurt) the popular (unpopular) product.

When $c \in [c, \min(c_S, c_M)]$, the first customer always visits a matching vendor, but will also visit a mismatching vendor if the private signal is $H$. Therefore, although a decision not to visit a
vendor implies an $L$ signal about that vendor, a decision to visit is not perfectly diagnostic of the signal behind. The second customer needs to assess to which extent the visit is driven by match, drawing on her knowledge that with probability $\theta$ the first customer is of the mainstream type $M$. Formally, suppose $v_M$ equals 1, the probability that the first customer visits vendor $M$ is

$$p(1|v_M = 1) = \theta \cdot p(1|v_M = 1, \text{match}) + (1 - \theta) \cdot p(1|v_M = 1, \text{mismatch}) = \theta \cdot 1 + (1 - \theta) \cdot p(H|v_M = 1) = \theta + (1 - \theta)q.$$ 

Similarly, $p(1|v_M = 0) = \theta \cdot p(1|v_M = 0, \text{match}) + (1 - \theta) \cdot p(1|v_M = 0, \text{mismatch}) = \theta \cdot 1 + (1 - \theta) \cdot p(H|v_M = 0) = \theta + (1 - \theta)(1 - q)$. By Bayes’ rule, after observing the first customer’s visit to vendor $M$ and before receiving her own signal, the second customer’s updated belief that $v_M$ equals 1 is given by

$$p(v_M = 1 | 1) = \frac{p(1|v_M = 1)p(v_M = 1)}{p(1|v_M = 1)p(v_M = 1) + p(1|v_M = 0)p(v_M = 0)} = \frac{p(1|v_M = 1)}{p(1|v_M = 1) + p(1|v_M = 0)}.$$ 

We can derive the second customer’s expected vertical quality of either vendor for either previous choice following the same logic. In summary,

$$E(v_M | 1) = \frac{\theta + (1 - \theta)q}{1 + \theta}, \quad E(v_N | 1) = \frac{(1 - \theta) + \theta q}{2 - \theta}, \quad E(v_M | 0) = E(v_N | 0) = 1 - q \quad (7)$$

The first part of Figure 2 plots the second customer’s updated prior quality expectation after observing the first customer’s choice. There are several comparisons to note. First, $1/2 < E(v_j | 1) < q$, $j \in \{M, N\}$. That is, although an earlier visit to a vendor is a positive quality cue, it is not as persuasive as the direct observation of an earlier $H$ signal since the visit could be partially attributed to match. Second, $E(v_M | 1) < E(v_N | 1)$ since $\theta > 1/2$. In other words, the positive quality implication of a visit to the mainstream vendor is not as strong as that of a visit to the niche vendor due to the mainstream vendor’s higher chance of matching consumer tastes. Third, $E(v_M | 1)$ decreases with $\theta$, while $E(v_N | 1)$ increases with $\theta$. This is because a higher chance of match attenuates quality inference for mainstream vendors, while for niche products, since they have a lower chance of a match, any visit has a strong implication of quality. Last, since the cost of visiting a vendor is sufficiently low, the decision not to visit is fully indicative.

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7 Proof: $\text{sign}(E(v_M | 1) - 1/2) = \text{sign}[(1 - \theta)(2q - 1)] > 0$ and $\text{sign}(E(v_M | 1) - q) = \text{sign}[\theta(1 - 2q)] < 0$ since $0 < \theta < 1$ and $q > 1/2$. The proof of $1/2 < E(v_N | 1) < q$ is similar.

8 Proof: $\text{sign}(E(v_M | 1) - E(v_N | 1)) = \text{sign}[(2\theta - 1)(1 - 2q)]$. 

10
of an $L$ signal for both vendors.

When $c \in [\max(c_S,c_M),\bar{c}]$, the first customer will visit a vendor if and only if it is the matching type and the signal is $H$. Therefore, although a visit unambiguously indicates an $H$ signal, the decision not to visit can be partially attributed to mismatch. The second customer’s quality perception can be derived in the same way as before:

$$E(v_M|1) = E(v_N|1) = q, \quad E(v_M|0) = \frac{1 - \theta q}{2 - \theta}, \quad E(v_N|0) = \frac{1 - (1 - \theta)q}{1 + \theta}$$

The second part of Figure 2 plots the second customer’s updated prior quality expectation after observing the first customer’s choice. It can be shown that $1 - q < E(v_M|0) < E(v_N|0) < 1/2$. This is, a decision not to visit a mainstream vendor carries more negative quality implication than a decision not to visit a niche one due to the lower chance of match for niche products. In addition, $E(v_M|0)$ decreases with $\theta$, while $E(v_N|0)$ increases with $\theta$. That is, a mainstream (niche) vendor’s increasing ease (difficulty) of match strengthens (dilutes) the negative quality implication of the lack of visit.

**Proposition 3.** Popularity information benefits niche products more than mainstream products. In particular, when the cost of visiting a vendor is sufficiently low ($c < \min(q, 1 - q + t)$), information on visits benefits niche vendors more. When the cost of visiting a vendor is sufficiently high ($c > \max(q, 1 - q + t)$), information on a lack of visits hurts mainstream vendors more.

In summary, popularity information may generate bandwagon effects that accelerate the rise of popular products and the fall of unpopular products. Such effects, however, are asymmetric between mainstream products and niche products. The apparent disadvantage of a niche product in matching customer tastes becomes its advantage in quality inference through the imperfect attribution process, accentuating favorable popularity information it receives, and reducing the damage of unfavorable popularity information.
Figure 2: Expected Vertical Quality with Popularity Information (assuming $q = 0.8$)

When $c \in [c, \min(c_S, c_M)]$

When $c \in [\max(c_S, c_M), \bar{c}]$

2.4 Herding and Aggregate Category Visits

Popularity information may lead to “herding,” where a customer ignores her private signal and repeats her predecessor’s decisions. Herding can generate two extreme outcomes: when the number of visitors to a vendor reaches a certain popularity level, all subsequent customers will visit this vendor regardless of their private signal and horizontal match (an “upward herd”); when the number of visitors falls below a minimum level, no subsequent customers will visit (a “downward herd”). Given its higher marginal quality inference per visit, a niche vendor benefits more from herding. Formally,

**Proposition 4.** Mainstream vendors require both a higher popularity level to induce an upward herd and a higher minimum traffic to avoid a downward herd than niche vendors.

Proof: See the Appendix.

Our results yield direct normative recommendations to category managers, multi-product firms, and platforms. First, popularity information can serve as a marketing tool to draw extra
traffic to the category. Recall that within the nontrivial cost range we focus on, no vendor achieves full market coverage (see Figure 1). However, when upward herding occurs, even a customer of the mismatching type with an unfavorable private signal will visit the vendor. Second, contrary to common belief that popularity information favors mainstream products, the marginal benefit of popularity turns out to be higher for niche vendors. Next, we empirically evaluate our predictions empirically through a controlled field experiment.

3 Field Experiment

3.1 Experimental Setting

We want to know how the availability of popularity information affects the likelihood of customers choosing mainstream and niche products or services. Using historical data to study the effect of population information availability presents problems, because websites’ decision whether to publicize popularity information can be linked to product characteristics in unobservable ways. For example, Tiffany.com does not display any popularity information and Amazon.com does. That does not mean it is credible to assume that any differences in the distribution of customer choices for jewelry bought from Amazon rather than Tiffany’s is due to Amazon’s easily accessible sales ranking information.

To address this endogeneity problem, we use field experiment data from a wedding portal website. This website experimented for two months with ways to update their alphabetical yellow page listing style. The website provided wedding vendor listings for a New England state.9 This website is representative of many online portals that bring together vendors and customers.

Theoretically, the wedding industry is attractive to study, because there is little prior consumption experience.10 Consequently, customers are likely to have imperfect information about

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9The geographic area that the website covered was representative of the US. The number of marriages in the state they operate in is in line with the national average. The only observable deviation from national trends is that wedding costs are around $10,000 greater in this state than the national average of $27,000.

10Even if an individual organizes successive weddings, they prefer to select different vendors in order to differ-
vendors, and observational learning may become a more important part of their decision making. This is also an industry where customers take vendor selection seriously. On average, 2.3 million weddings take place in the US each year, accounting for $72 billion in annual wedding expenditures. Most brides invest considerable efforts in selecting vendors. During an average 13-month engagement, eight hours a week is spent planning.\textsuperscript{11} A bride spends on average $967 on flowers, $1,276 on bridal attire, and $7,330 on the reception.\textsuperscript{12}

It is important to be clear that we are not expecting popularity information to increase the demand for weddings. Instead, we are interested in how popularity information affects customers’ decisions to click on the URL of the listed vendor. Popularity information may attract clicks from customers who would otherwise have chosen to seek wedding services from other channels, such as a national chain or a department store, rather than visiting one of the stand-alone vendors listed on the website. This is supported by confidential information provided to us by the website suggests that a sizable proportion of visitors go to the listing page without ever following a link to a vendor, suggesting that for brides the decision to visit these vendor websites is not trivial or automatic. In other words, though the total number of weddings can stay constant, popularity information might shift the number of vendors that brides show interest in when visiting this particular website.

The website does not provide extensive information about vendors. It lists only the vendors’ name, location and telephone number. We exploit the information on location to inform horizontal match between vendors and consumers. We define as “mainstream” vendors who are located in the major and only metropolitan statistical area in the state. We define as “niche” vendors located in the outlying, more rural communities. Our use of location to inform what is a niche product and what is not has three advantages. First, this is a fairly literal interpretation of the existing class of hoteling models of horizontal differentiation that are predicated

\textsuperscript{11}Source: Association of Bridal Consultants from Bride’s Magazine reader survey
\textsuperscript{12}Source: American Wedding Study, 2002
on transportation costs. Second, the provision of location information is expected and does not focus attention unduly on the niche/mainstream distinction that we study. Third, we do not rely upon a subjective definition of niche/mainstream that could evolve or change during our study (for example, rap music was a niche product in the eighties and a mainstream product by the nineties, as it increased in popularity.)

3.2 Experimental Design and Procedures

The website explored a variety of ways that it could present information about the popularity of each vendor. The site owners measured the popularity of a vendor by the number of previous clicks its link had received.\textsuperscript{13} The website conducted this experiment using four out of a total of 19 wedding service categories that received the most traffic and had the largest number of listings: Caterers, Reception Halls, Bridal Attire and Florists. These four categories were randomly allocated into three experimental conditions and one unchanged control condition.

Table 1 summarizes the assignment and the pre-experiment traffic level of the four categories. We witnessed and verified the randomness of this allocation. Florists were the control category and retained their alphabetic ordering with no display of clicks. Reception halls retained their alphabetical ordering but displayed information about previous clicks. Caterers displayed no information about previous clicks but were listed by the number of previous clicks, with the vendor receiving the most clicks being listed first. Bridal shops not only had the number of prior clicks displayed, but were also ranked in descending order of popularity.

The nature of the field experiment means that we use different wedding services as controls for each other in a field experiment. This cross-category control would be problematic if we were studying an apparel retailer and we were trying to use interest in, say, sweaters to predict the interest in bathing suits. However, in the wedding industry different categories of services, such

\textsuperscript{13} As discussed by Baye, Morgan, Gatti, and Kattuman (2006), the number of clicks puts an upper limit on the distribution of demand.
as catering and florists, are complementary components of the ultimate end wedding product. Therefore, it seems plausible to assume that these categories share similar unobserved shocks over time, and provide a “level playing field” upon which to measure treatment effects.

The field experiment ran for two months, from August to September 2006. The number of previous clicks was calculated using a base date of six months prior to the field experiment. The website did not disclose to visitors any information about the start date for this stock of clicks. This lack of disclosure resembles the practice of other firms, and it also means that customers are not confused by additional cues such as seasonality. The number of clicks is put in an extra cell of the html table for each vendor, in a column entitled “clicks.” In the control condition, this column was unlabeled and empty. There is no difference in the webpage format across conditions, except for the display of click information. Every three days we ran a screen-scraping program to verify our data and ensure that there were no glitches in the experiments.

We were also concerned about cross-contamination between categories if subjects visit them sequentially. For example, brides could first visit the bridal attire listings and then visit listings for caterers but at that stage be able to guess that these listings were ordered by popularity. Such behavior would lead us to underestimate the effect of popularity information in the results where we exploit the display of information as our exogenous source of identification. However, we obtained confidential statistics that suggested that most visitors to a listings page arrived there directly from search engines rather than navigating there from within the website.

4 Empirical Analysis

4.1 Data

The firm collected data on browsing behavior based on their Apache Web Server logs. To protect the privacy of their users, they removed IP address information and created a dataset they could share with us. In this dataset, each observation is a time-stamp for when a link received a click,
Table 1: Experiment Design

<table>
<thead>
<tr>
<th></th>
<th>Popularity Ranking</th>
<th>Clicks Displayed</th>
<th>Mean Daily PreTest Clicks</th>
<th>Mean Cumulative Clicks</th>
<th>Change in Daily Clicks from Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bridal Shops</td>
<td>Yes</td>
<td>Yes</td>
<td>5.2</td>
<td>441.7</td>
<td>0.48***</td>
</tr>
<tr>
<td>Reception Halls</td>
<td>No</td>
<td>Yes</td>
<td>6.6</td>
<td>540.5</td>
<td>-0.31***</td>
</tr>
<tr>
<td>Caterers</td>
<td>Yes</td>
<td>No</td>
<td>3.0</td>
<td>243.7</td>
<td>0.18**</td>
</tr>
<tr>
<td>Florists</td>
<td>No</td>
<td>No</td>
<td>2.6</td>
<td>201.8</td>
<td>-</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

alongside the vendor details and category that received this click. There were several minor challenges in processing the data that we describe in the empirical appendix. The data span the two months prior to the field experiment (June and July 2006) and the two months of the field experiment (August and September 2006). During these four months, there were 860,675 clicks across all categories. The four categories in our experiment accounted for 515,121 of these clicks. There is a total of 346 vendors listed within the four selected categories: 52 in florists, 155 in reception halls, 66 in caterers, and 73 in bridal shops. While the average vendor received 4.9 clicks each day, there were a few “popular” vendors who received over 15 clicks a day, together with a long tail of less popular vendors receiving only 1 click a day. Niche vendors on average received 0.3 less clicks per day than mainstream vendors (significant at the 1 percent level).

4.2 Graphical Analysis: Aggregate Shifts

As an initial exploration of the data, we performed graphical analysis of the clicks in the different conditions. Figure 3 compares the effect on the distribution of clicks for the control condition (corresponding to the traditional yellowpages style of listing) where nothing changed, relative to the other three conditions. For ease of comparison we detrend the category data, order the vendors by number of cumulative clicks, and compare pre- and post-clicks on the same graph. While there was little difference for the control condition, there was an increase in the average number of clicks for the most popular vendors in the top quintile in the condition where popularity
information was both displayed and highlighted by the ranking.

In Table 1 we report the estimated aggregate effect of each of the conditions after controlling for each day of the week, week and vendor. These suggest that on average, the condition where clicks were displayed and vendors were ranked showed the most improvement, with an increase of 0.48 clicks per vendor. The condition where vendors were ranked showed a smaller increase of just 0.18 per vendor. One unexpected finding is that, relative to other categories, reception halls (where clicks were displayed and vendors were listed alphabetically) had 0.31 fewer daily clicks per vendor. This negative effect persists for all reception halls - it is not concentrated for either the more popular or less popular vendors. This suggests that brides were put off using the reception halls section of the website, as opposed to a shift of demand within the reception halls category. There are two potential explanations for this: First, a website which displays clicks but does not rank clicks may appear unprofessional, signaling an unattractive lack of technical know-how. Second, the reception halls category was unusual in that it had several vendors whose initial character was a number, for example, “110 Broadway.” Vendors with numerical names were unpopular with brides, which meant that the first few listings had fewer than 25 percent of the average number of clicks in the category. That low number of clicks may have put brides off what appeared to be a low-traffic website. Given these category-specific issues, we present results including and excluding the reception halls condition. Our focus on between-vendor rather than category effects means that this peculiarity does not change our results.

For internet portal sites who want to increase all clicks within a category, our results suggest that publicizing popularity information and making such information salient through popularity-based ranking is the best strategy. The remaining question is what kind of products or vendors this popularity information benefits the most.
4.3 Specification

We estimate a model specification that captures the effect of being popular on how interested customers are in that vendor. Our dependent variable is the daily amount of clicks that a vendor receives. We want to find out how this is affected by popularity information, and how the effect of popularity information is affected by niche status. We measure popularity, as it was on the website, by cumulative number of previous clicks ($\text{PrevClicks}$). We identify the effect of this popularity information by exploiting the fact that this information was only provided in two of the conditions. We also exploit exogenous variation in prior clicks generated by the initial alphabetical listing to check the robustness of our estimates using instrumental variables.
We estimate the main effect of previous popularity, $PrevClicks$, on vendor choice. This allows us to see whether popular vendors are becoming more or less popular in general, independently of whether customers know their popularity. To capture the level effect of popularity information for both niche and mainstream vendors we include a dummy $Displayed_{jt}$ that is equal to one for vendors whose click information was displayed. To capture the effect of how a vendor’s popularity affects the effect of popularity information we include an interaction between whether clicks are displayed and the number of previous clicks $PrevClicks_{jt} * Displayed_{jt}$. Last, we include a further interaction term $PrevClicks_{jt} * Displayed_{jt} * Niche_{j}$ to pick up whether there is an incremental effect on the effect of popularity information for niche vendors.

We also control for systematic differences in customer click behavior across vendors and across time.\textsuperscript{14} We include vendor-specific fixed effects $\alpha_j$ for each vendor $j$ to control for static differences in base demand. It is also likely that the propensity of brides to make vendor selections changes over time. We capture this changing time trend for vendor-interest by a vector $X_{jt}$ of weekly dummies and day-of-week dummies. $X_{jt}$ also contains a dummy for whether this is the treatment period or not, and an interaction between this dummy and whether the product $j$ is a niche product. Our identifying assumption for the time trend is that all categories would have had similar time trends in clicks if it had not been for the experimental intervention.

Finally we include a variable $PagePos_{jt}$ to pick up the “website real estate” effect. This page location effect could occur either because customer incur high search costs from scrolling, or because customers’ eyes are drawn to the top listings.

Equation 9 summarizes our specification, where $\alpha_j$ and the $\beta$s are parameters to be estimated.

\begin{equation}
\text{clicks}_{jt} = \alpha_j + \beta_0 X_{jt} + \beta_1 PagePos_{jt} + \beta_2 PrevClicks_{jt} + \beta_3 Displayed_{jt} + \beta_4 PrevClicks_{jt} * Displayed_{jt} + \beta_5 PrevClicks_{jt} * Displayed_{jt} * Niche_{j} + \epsilon
\end{equation}

\textsuperscript{14}Though we use field experiment data, our use of a full set of fixed effects and focus on interactions is similar to the differences-in-differences approach used in Chevalier and Mayzlin (2006) and Anderson, Fong, Simester, and Tucker (2007).
The particular specification we estimate is linear in these variables. We have tried other specifications (such as logarithmic transformations) with similar results.

### 4.4 Results and Robustness Checks

The first column of Table 2 presents our initial results for all vendors. \( \text{PrevClicks}_{jt} \times \text{Displayed}_{jt} \) is positive and significant. This suggests that the more popular the vendor, the larger the effect that the display of popularity information has. To improve readability of the tables \( \text{PrevClicks} \) is measured in 100s of clicks. Therefore a coefficient estimate of 0.17 means that if a vendor has 200 clicks and popularity information is displayed then they can expect to receive 0.34 more

<table>
<thead>
<tr>
<th>Sample</th>
<th>All Vendors</th>
<th>Ranked Only</th>
<th>Ranked Only</th>
<th>Ranked Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>Daily Data</td>
<td>Daily Data</td>
<td>2-Period Data</td>
<td>14-Day Window</td>
</tr>
<tr>
<td>PrevClicks<em>Displayed</em>Niche (( \beta_3 ))</td>
<td>0.097* (0.056)</td>
<td>0.146** (0.067)</td>
<td>0.482* (0.248)</td>
<td>10.334** (4.578)</td>
</tr>
<tr>
<td>PrevClicks*Displayed (( \beta_4 ))</td>
<td>0.174*** (0.053)</td>
<td>0.182* (0.106)</td>
<td>1.416*** (0.397)</td>
<td>9.856 (8.807)</td>
</tr>
<tr>
<td>Displayed (( \beta_3 ))</td>
<td>-0.408** (0.178)</td>
<td>-0.431* (0.248)</td>
<td>-3.824*** (0.664)</td>
<td>-27.546 (20.746)</td>
</tr>
<tr>
<td>PrevClicks (( \beta_2 ))</td>
<td>-0.410*** (0.074)</td>
<td>-0.194* (0.114)</td>
<td>-12.471*** (2.520)</td>
<td>-12.157 (10.146)</td>
</tr>
<tr>
<td>PagePos (( \beta_1 ))</td>
<td>-0.019*** (0.005)</td>
<td>-0.014*** (0.005)</td>
<td>-0.056*** (0.012)</td>
<td>-1.018*** (0.374)</td>
</tr>
<tr>
<td>Observations</td>
<td>36656</td>
<td>13456</td>
<td>1508</td>
<td>232</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.08</td>
<td>0.07</td>
<td>0.28</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Vendor Fixed Effects | Yes | Yes | Yes | Yes
Weekly Dummies | Yes | Yes | No | Yes
Day of Week Dummies | Yes | Yes | No | Yes
Niche Time Trend | Yes | Yes | Yes | Yes

Dependent Variable: Number of clicks
Robust Standard Errors: * \( p<0.10 \), ** \( p<0.05 \), *** \( p<0.01 \)
clicks each day by virtue of this effect.

\( \text{PrevClicks}_{jt} \times \text{Displayed}_{jt} \times \text{Niche} \) is positive and significant. Since this is an incremental effect, this implies that popularity information has a larger effect for niche vendors than that for mainstream vendors. The model in section 2 presents a potential explanation for this finding. Website browsers expect vendors in the major urban area (mainstream vendors) to be busy and vendors in rural areas (niche vendors) to be less busy. Therefore when browsers see a vendor in a rural area with a large number of clicks they are more likely to make a quality inference, than a vendor with a large number of clicks in the city.

\( \text{Displayed}_{jt} \) is negative in all specifications. As a baseline, a vendor with zero clicks displayed will lose approximately 0.41 clicks a day as a result of their popularity information being displayed. When taken in conjunction with the estimate for \( \text{PrevClicks}_{jt} \times \text{Displayed}_{jt} \), this implies that only the mainstream vendors that have over roughly 240 clicks see an increase in clicks from the release of popularity information. However, the positive estimate for \( \text{PrevClicks}_{jt} \times \text{Displayed}_{jt} \times \text{Niche} \) of 0.10 suggests that this threshold is closer to 150 clicks for niche vendors.

The coefficient on \( \text{PrevClicks}_{jt} \) is negative. Our vendor fixed effects capture the differences across vendors in baseline popularity, so this negative coefficient suggests that temporary increases in previous clicks above a vendor’s baseline level are followed by periods of decrease in clicks, regardless of whether popularity information is released. The (unreported) coefficients for the time trend are much as expected. They indicate a decrease in activity over the Labor Day weekend and a high level of websurfing on Mondays. The time trend for niche-products is negative and marginally significant compared to mainstream products. \( \text{PagePos}_{jt} \) is also negative, suggesting that independently of the release of popularity information, vendors who are listed first receive more clicks than vendors displayed lower down the page.

The first column of Table 2 present results for all vendors, irrespective of how they are
arranged on the page. The second column focuses analysis on caterers and bridal salons who were arranged by popularity. In these results, the boost from popularity and the boost for niche vendors is greater than in the pooled results. We speculate this could be because the ranking makes the popularity information particularly salient, and in line with the elaboration-likelihood model this increases both opportunity and motivation for information processing.\textsuperscript{15} We focus our subsequent analysis on the two conditions where the vendors were ranked, to abstract from the idiosyncratic aggregate shock to the reception halls category.

4.5 Specification Checks

When using a panel data set where there is just one policy experiment, such as in our data, the level of significance of the estimates should be interpreted with care (see Bertrand, Duflo, and Mullainathan (2004)). Repeated use of the same exogenous change in variables can lead researchers to overstate the significance of the estimates. To address this concern, we used two broadly accepted techniques. First, as suggested by (Hausman, Hall, and Griliches 1984), we tried a Poisson quasi-maximum likelihood specification with conditional fixed effects and clustering at the vendor level that had qualitatively similar results. Second, we experimented with different time frames. In the third column of Table 2, we present results from regressions where we combined our daily data into a pre-period and a post period. $PrevClicks_{jt}$ is now the mean of the cumulative clicks displayed for the vendors. The results, in particular the positive and significant coefficient on $PrevClicks_{jt} \times Displayed_{jt} \times Niche$, support our previous finding that the display of popularity information has the largest effect for popular vendors.

In the estimates presented in the fourth column of Table 2, we reduce the time window of estimation and evaluate changes in click behavior for the week before the field experiment and the week after the experiment. These estimates are similar to our previous results in the first two columns of Table 2. The advantage to this regression discontinuity approach is that it allows

\textsuperscript{15}We thank an anonymous referee for this point.
Table 3: Responses to Previous Clicks: Robustness checks using instrumental variables

<table>
<thead>
<tr>
<th>Approach</th>
<th>Sample</th>
<th>OLS</th>
<th></th>
<th>Instrumental Variables</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Niche</td>
<td>Mainstream</td>
<td>Niche</td>
<td>Mainstream</td>
</tr>
<tr>
<td>PrevClicks</td>
<td></td>
<td>1.273***</td>
<td>1.078***</td>
<td>0.852***</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.020)</td>
<td>(0.029)</td>
<td>(0.161)</td>
<td>(0.304)</td>
</tr>
<tr>
<td>Partial First Stage Results</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Position in Alphabet</td>
<td></td>
<td>-0.079***</td>
<td>-0.043***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)</td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td>1995</td>
<td>1938</td>
<td>1995</td>
<td>1938</td>
</tr>
<tr>
<td>R-Squared</td>
<td></td>
<td>0.67</td>
<td>0.44</td>
<td>0.60</td>
<td>0.07</td>
</tr>
<tr>
<td>Weekly Dummies</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Day of Week Dummies</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Dependent Variable: Number of clicks
Sample: Vendors in Bridal Salon Category
* p<0.10, ** p<0.05, *** p<0.01

us to evaluate whether serial correlation is an alternative driver of our results. The concern is that there could be a time-varying shock which affects rural bridal salons and no other vendors. For example, there could have been growing word of mouth about the bargains to be had at non-urban bridal stores. This would increase both the stock of clicks and the propensity to click through for rural bridal stores (the niche vendors who had their clicks displayed). Our identification logic follows that put forward by Black (1999), Hahn, Todd, and Van der Klaauw (2001), and Busse, Silva-Risso, and Zettelmeyer (2006), that by taking a very short time window we reduce the likelihood that such a time-varying shock (other than the experimental treatment) could explain the results.

As a further robustness check, we used instrumental variables to address serial correlation. Here we exploit the fact that initially the vendors were ranked alphabetically. It seems reasonable that the position in the alphabet of the first letter of a vendor’s name should be unrelated to its popularity when the vendors are ranked by popularity rather than alphabetically. The alphabetical ordering in the pre-test period, however, could have led to vendors who begin with
an A to have a higher stock of clicks than vendors who began with a Z, for reasons unrelated to customer perceptions in the treatment period. This suggests that the alphabetical ordering of the vendors is a potential instrumental variable for the treatment period.

Our results are reported in Table 3. We stratify our estimates for the effect of $\text{PrevClicks}$ by whether a vendor is niche or mainstream using the subsample of results for vendors where popularity information was displayed and vendors were ranked by popularity. Using this subsample allows us to check the robustness of our previous distinction between $\text{PrevClicks}_{jt} \times \text{Displayed}_{jt} \times \text{Niche}$ and $\text{PrevClicks}_{jt} \times \text{Displayed}_{jt}$ with a single instrument. The instrumental variable results reinforce the results in Table 2. The effect of $\text{PrevClicks}$ for niche vendors is positive and significant. The point estimate for mainstream vendors is smaller, and insignificant. These results again suggest that the effect of popularity information is larger for niche vendors. The first stage results support our choice of instrument and suggest that there is a negative and significant effect from alphabetical position on the total number of clicks displayed. A vendor that begins with Z and is consequently in 26th position has a lower number of displayed clicks, than a vendor that begins with an A and is in the 1st position. The Anderson canonical correlation likelihood ratio test tells us that this instrumental variables strategy identify our equation.

Further qualitative robustness checks that we conducted into time-varying shocks at the wedding industry level are reported in the empirical appendix.

5 Further Robustness Check: A Lab Experiment

We conducted a follow-up laboratory experiment to achieve the following goals. First, we wanted to check the robustness of the effects of popularity information release with a pure between-subjects experimental design. Although our field experiment aims to implement a between-subjects design, it cannot rule out the possibility that a website user may visit multiple categories and therefore migrates across different treatment conditions. If the same user’s choice behavior is positively correlated across categories, the treatment effect can be underestimated. In Study 2,
we address this potential problem by assigning subjects into and confining them within different treatment conditions. Second, we want to investigate the reasons why the less popular vendors are still being visited. Towards this goal, we introduce another source of exogenous variation: in addition to choosing whether to release popularity information, we manipulate the degree of popularity to claim. We are thus able to test the theoretical hypothesis that horizontal differentiation moderates the amount of vertical inference drawn from past popularity. Third, we explicitly give subjects the option to choose multiple products or nothing from the category. By doing so, we obtain a direct measure of category demand and its composition. Fourth, to examine whether the theoretical insights apply beyond internet-based markets where clicks volume is a key outcome variable, in the lab experiment we present an off-line product choice setting and elicit subjects’ actual purchase tendency.

5.1 Experimental Design and Procedures

We use three parallel experimental conditions. Condition 1 describes the choice setting without supplying any popularity information:

Imagine you need to buy a packet of cookies from either of two local bakeries: the “Chocolate Cookie Emporium,” and the “Butter Scotch Cookie Shop.” Both bakeries sell the cookies for $9.99 a packet. Please circle your choice:

a) Buy a packet of cookies from the Chocolate Cookie Emporium
b) Buy a packet of cookies from the Butter Scotch Cookie Shop
c) Buy a packet of cookies from each bakery
d) Buy from neither bakery

Condition 2 differs from condition 1 by supplementing the choice question with popularity information. Specifically, before asking the subject to circle their choice, condition 2 states:

By this time of the day the Chocolate Cookie Emporium has sold 68 packets, and
the Butter Scotch Cookie Shop has sold 36 packets.

Condition 3 is identical to condition 2 except for the population information statement, which changes to:

By this time of the day the Chocolate Cookie Emporium has sold 36 packets, and the Butter Scotch Cookie Shop has sold 68 packets.

Our use of the bakery category accommodates both vertical quality and horizontal match as potential decision drivers. While information on vertical quality is minimal and is identical across bakeries, the names of the two bakeries evoke different horizontal attributes which cater to different consumer tastes. It is also plausible for bakery consumers to have a common perception of which product varieties serve a mainstream market (e.g., chocolate cookies) and which serve a niche market (e.g., butter scotch cookies).

Condition 1 allows us to verify that chocolate cookies are indeed the mainstream product, and measure the relative size of the mainstream market and the niche market as a benchmark. We then measure the change in market size in conditions 2 and 3 to identify the effect of releasing popularity information. The number of packets sold, 68 and 32, are random. Conditions 2 and 3 are symmetric in the sense that they are identical except for swapping the number of sold packets claimed for the two bakeries. The same past sales volume, however, may signal higher vertical quality for niche products than for mainstream products, as predicted by Proposition 2. Conditions 2 and 3 allow us to find out whether this seeming symmetric popularity information leads to asymmetric subsequent choice outcomes.

One hundred and two undergraduate students at an East Coast university participated in the experiment. Subjects were assigned randomly into one of the three conditions, with 33 in condition 1, 35 in condition 2, and 34 in condition 3. Actions were taken to prevent communication between subjects.
Table 4: Lab Experiment Results

Number of Subjects Choosing Each Option

<table>
<thead>
<tr>
<th></th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chocolate Cookie Emporium only</td>
<td>19</td>
<td>24</td>
<td>6***</td>
</tr>
<tr>
<td>Butter Scotch Cookie Shop only</td>
<td>7</td>
<td>4</td>
<td>16**</td>
</tr>
<tr>
<td>Both bakeries</td>
<td>2</td>
<td>3</td>
<td>7*</td>
</tr>
<tr>
<td>Neither bakery</td>
<td>5</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Total number of subjects</td>
<td>33</td>
<td>35</td>
<td>34</td>
</tr>
</tbody>
</table>

Demand Decomposition

<table>
<thead>
<tr>
<th></th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chocolate Cookie Emporium</td>
<td>21</td>
<td>27</td>
<td>13**</td>
</tr>
<tr>
<td>Butter Scotch Cookie Shop</td>
<td>9</td>
<td>7</td>
<td>23***</td>
</tr>
<tr>
<td>Total demand</td>
<td>30</td>
<td>34</td>
<td>36</td>
</tr>
</tbody>
</table>

Note: The significance statistics are obtained from t-tests of the null hypothesis that a number is equal to the corresponding number in condition 1.

*p < 0.10, **p < 0.05, ***p < 0.01

5.2 Experimental Results

Table 4 summarizes the number of subjects choosing each option (either bakery, both, or neither) and the number of packets demanded from each bakery across the three conditions. In condition 1, there is a demand for 21 packets of chocolate cookies, significantly different from 9, the demand for butter scotch cookies ($t = 2.540, p = 0.016$). Therefore, chocolate cookies constitute the mainstream product and butter scotch cookies the niche product.

In condition 2, the number of packets demanded for chocolate cookies becomes 27, not significantly different from the number 21 in condition 1 ($t = -1.217, p = 0.228$). Similarly, the number of packets demanded for butter scotch cookies is 7, not significantly different from the benchmark number of 9 ($t = 0.699, p = 0.487$). Therefore, the information that the mainstream
product has been more popular does not significantly influence choices.

In condition 3, the number of packets demanded for chocolate cookies is 13, significantly lower than the benchmark number of 21 ($t = 2.117, p = 0.038$). At the same time, the number of packets demanded for butter scotch cookies rises sharply to 23, significantly higher than the benchmark number of 9 ($t = -3.562, p = 0.001$). In sharp contrast with condition 2, when the niche product has been more popular, releasing such popularity information boosts the sales of the niche product dramatically and brings down the sales of the mainstream product.

In sum, the lab experiment supports our central result that the marginal benefit of popularity is greater for niche products.

6 Conclusion

In this paper we ask how the efficacy of popularity information varies in usefulness as a marketing tool with whether the product is niche or mainstream. The conventional view is that popularity information benefits mainstream products through superstar effects: Mainstream products are high-volume and consequently create the largest bandwagons. We propose an opposing view, that popularity information may actually be of greater benefit to niche products. The fact that niche products are less likely to attract customers due to their small chance of matching customer tastes means that the customers they do attract convey a stronger quality signal.

To explore these opposing predictions, we use data from a field experiment conducted by a website that lists wedding service vendors. We find that the effect of releasing popularity information is greatest for popular vendors in outlying rural areas away from the major urban center. The finding supports our prediction that brides are more likely to infer high quality if a vendor has been chosen by multiple other brides despite the fact that it is difficult to get to. We check the robustness of our results using a regression discontinuity approach and instrumental variables and find that this main result holds. We conduct a further lab experiment to rule
out potential confounds introduced by field experiments, and replicate the finding that niche products benefit more from information that they are popular.

These findings contribute to our understanding of how popularity information affects the long tail of e-commerce. Although automated “web 2.0” type tools which highlight previous consumer choices seem to benefit mainstream products, our results suggest that these popularity tools can actually benefit the niche products that compose the long tail.

There are several potential ways of building on this research. One possibility is to explore whether popularity information has similar differentiated effects on other marketing mix variables. For example, will popular products with higher prices benefit more from the release of popularity information than popular products with lower prices? If indeed consumers infer superior quality to justify the high price tag, what would be the firm’s optimal pricing strategy? Another potential avenue for future research is to explore how popularity information affects the distinction between niche and mainstream products in the customer’s mind. While in this study we model quality and match as orthogonal constructs, and are careful to choose plausibly exogenous differentiators such as distance, it is easy to imagine other product characteristics (such as the width of pants legs) that could be endogenously categorized as niche or mainstream depending on the social norm of the day, which in turn derives from established popularity.
7 Appendix

7.1 Deriving Herding Thresholds

In this section, we derive the herding thresholds mathematically, and show that mainstream vendors require both a higher popularity level to induce an upward herd and a higher minimum traffic to avoid a downward herd.16

Suppose \( n \) customers have made their independent visit decisions without popularity information, as modeled in Section ??\(^7\). Let \( n_j, j \in \{M, N\} \) denote the number of visits that vendor \( j \) has received from these \( n \) potential customers. When \( n \to \infty \), \( n_j/n \) approaches vendor \( j \)'s *ex ante* visit probability, which depends on this vendor's true vertical quality, horizontal type, and the costs of visit, as summarized in Table 5. Below, we investigate how the popularity information about vendor \( j \), as represented by the \( n \) and \( n_j \) pair, influences subsequent customer choices.

Table 5: Visit Probability without Popularity Information

<table>
<thead>
<tr>
<th>Vertical quality</th>
<th>Horizontal type</th>
<th>( c \in (c_S, c_M) )</th>
<th>( c \in (c_S, c_M) )</th>
<th>( c \in [c, \min(c_S, c_M)] )</th>
<th>( c \in [\max(c_S, c_M), c] )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 1 )</td>
<td>Mainstream</td>
<td>( \theta )</td>
<td>( q )</td>
<td>( \theta + (1 - \theta)q )</td>
<td>( \theta q )</td>
</tr>
<tr>
<td>( 0 )</td>
<td>Mainstream</td>
<td>( \theta )</td>
<td>( 1 - q )</td>
<td>( \theta + (1 - \theta)(1 - q) )</td>
<td>( \theta(1 - q) )</td>
</tr>
<tr>
<td>( 1 )</td>
<td>Niche</td>
<td>( 1 - \theta )</td>
<td>( q )</td>
<td>( (1 - \theta) + \theta q )</td>
<td>( (1 - \theta)q )</td>
</tr>
<tr>
<td>( 0 )</td>
<td>Niche</td>
<td>( 1 - \theta )</td>
<td>( 1 - q )</td>
<td>( (1 - \theta) + \theta(1 - q) )</td>
<td>( (1 - \theta)(1 - q) )</td>
</tr>
</tbody>
</table>

**Case 1:** When \( c \in (c_S, c_M) \), which requires \( 1 + t > 2q \), the \( n \) early customers’ visit decisions have been solely determined by match. Therefore, releasing such popularity information does not change subsequent customers’ visit decisions, which will continue to be solely driven by match. Among all subsequent potential customers, a fraction \( \theta \) will visit the mainstream vendor, and a fraction \( 1 - \theta \) will visit the niche vendor, regardless of the private signals.

\[\text{16} \text{For exposition simplicity, we only report the thresholds for a vendor to attract all subsequent customers or lose all of them. The model can be easily extended to obtain the popularity level for a vendor to attract all matching subsequent customers, and the minimal traffic below which a vendor loses all subsequent customers of the mismatching type.}\]
Case 2: When $c \in (c_M, c_S)$, which requires $1 + t < 2q$, each of the $n$ customers visits a vendor upon a high private signal, regardless of the vendor’s horizontal type. Therefore, the probability of a visit equals $q$ if the vendor’s vertical quality is 1, and $1 - q$ if the vendor’s vertical quality is 0. Since private signals are i.i.d. distributed conditional on the true vertical quality level, the total visit frequency $n_j$ follows a binomial distribution with parameters $(n, q)$ if vertical quality is 1, and $(n, 1 - q)$ if vertical quality is 0. For any subsequent customer exposed to the popularity information that vendor $j$ has received $n_j$ visits out of $n$ potential customers, her updated prior expectation of $v_j$ is

$$E(v_j | n_j, n) = \frac{p(n_j, n | v_j = 1)p(v_j = 1)}{p(n_j, n | v_j = 1)p(v_j = 1) + p(n_j, n | v_j = 0)p(v_j = 0)}$$

$$= \frac{q^{n_j}(1-q)^{n-n_j}/2}{q^{n_j}(1-q)^{n-n_j}/2 + (1-q)^{n_j}q^{n-n_j}/2}$$

$$= \frac{1}{1 + (\frac{q}{1-q})^{n-2n_j}}$$

Following the same formula, if in addition this customer receives an $H$ private signal about vendor $j$, her posterior expectation of $v_j$ becomes

$$E(v_j | n_j, n, H) = \frac{1}{1 + (\frac{q}{1-q})^{n-2n_j-1}}$$

If instead she receives an $L$ private signal about vendor $j$, her posterior expectation of $v_j$ becomes

$$E(v_j | n_j, n, L) = \frac{1}{1 + (\frac{q}{1-q})^{n-2n_j+1}}$$

This customer will visit vendor $j$ if her posterior expectation of $v_j$ plus any match utility is greater than the cost $c$, where $1 - q + t < c < q$. An interesting scenario is when $E(v_j | n_j, n, L) > q$, so that the customer will always visit vendor $j$ regardless of her private signal and horizontal match. This visit decision thus contains no quality information to subsequent customers, who
will all visit vendor $j$ regardless of their private signals and horizontal type. Formally, when
\[ n_j > \bar{n} = \frac{n}{2} + 1 \tag{10} \]
releasing popularity information about vendor $j$ will attract all subsequent customers to visit vendor $j$.\footnote{Proof: $E(v_j|n_j, n, L) > q \iff (1 - q)^{n - 2n_j + 2} > q^{n - 2n_j + 2} \iff n - 2n_j + 2 < 0$ since $q > 1/2.$} Similarly, when
\[ n_j < \underline{n} = \frac{n}{2} - 1 \tag{11} \]
$E(v_j|n_j, n, H) + t < c_M$, so that no subsequent customer will visit vendor $j$ regardless of her private signal and horizontal match.

**Case 3:** When $c \in [c, \min(c_S, c_M)]$, $n_j$ again follows a binomial distribution with the “success” probability equal to the visit probability given in Table 5. For any subsequent customer exposed to the popularity information, her updated prior expectation of the mainstream vendor’s vertical quality is
\[ E(v_M|n_M, n) = \frac{1}{1 + (\frac{1-q+\theta_q}{1-q-\theta_q})^{n_M}(\frac{q}{1-q})^{n-n_M}} \]
while her updated prior expectation of the niche vendor’s vertical quality is
\[ E(v_N|n_N, n) = \frac{1}{1 + (\frac{1-\theta_q}{1-\theta-\theta_q})^{n_N}(\frac{q}{1-q})^{n-n_N}} \]
It can be shown that for any $n_M = n_N > 0$, $E(v_M|n_M, n) < E(v_N|n_N, n)$. That is, the same number of visits implies higher vertical quality for niche products. Furthermore, suppose this subsequent customer also receives an $L$ signal on the mainstream product. Her posterior expec-
The evaluation of $v_M$ becomes

$$E(v_M|n_M, n, L) = \frac{1}{1 + \left(\frac{1-q+q\theta}{\theta q-\theta q}\right)^{n_M} \left(\frac{q}{1-q}\right)^{n-n_M+1}}$$

We are interested in the condition for $E(v_M|n_M, n, L)$ to be greater than all allowed $c$ values. It can be shown that a subsequent customer would visit the mainstream vendor regardless of her private signal and horizontal match when

$$n_M > \bar{n}_M = \frac{x_1}{x_1 + x_2} (n + 2) \quad (12)$$

and that no subsequent customer will visit the mainstream vendor when

$$n_M < \underline{n}_M = \frac{nx_1 - x_1 - x_t}{x_1 + x_2}, \quad t < 1 - q \quad (13)$$

where $x_1 = \ln \left(\frac{q}{1-q}\right)$, $x_2 = \ln \left(\frac{\theta + q - \theta q}{1+\theta q - q}\right)$, and $x_t = \ln \left(\frac{q + t}{1-q-t}\right)$.

Similarly, all subsequent customers would visit the niche vendor when

$$n_N > \bar{n}_N = \frac{x_1}{x_1 + x_3} (n + 2) \quad (14)$$

and no subsequent customer would visit the niche vendor when

$$n_N < \underline{n}_N = \frac{nx_1 - x_1 - x_t}{x_1 + x_3}, \quad t < 1 - q \quad (15)$$

where $x_3 = \ln \left(\frac{1-\theta + \theta q}{1-\theta q}\right)$.

There are several comparisons to note. It can be verified that $0 < x_2 < x_3 < x_1 < x_t$. Therefore, for the nontrivial case where $\bar{n}_M$ and $\underline{n}_N$ are positive (i.e., where $n > 1 + x_t/x_1$)

$$\bar{n}_N < \bar{n}_M, \quad \text{and} \quad \underline{n}_N < \underline{n}_M \quad (16)$$
Furthermore, since $\frac{\partial^2 x_3}{\partial \theta^2} < 0$ and $\frac{\partial^3 x_3}{\partial \theta^3} > 0$,

\[
\frac{\partial \bar{n}_M}{\partial \theta} > 0, \quad \frac{\partial \bar{n}_N}{\partial \theta} < 0, \quad \frac{\partial n_M}{\partial \theta} > 0, \quad \frac{\partial n_N}{\partial \theta} < 0
\]

**Case 4**: When $c \in [\max(c_S, c_M), \bar{c}]$, we can derive the threshold levels using the same strategy.

In summary,

\[
\bar{n}_M = \frac{x_1 + nx_3 + x_t}{x_1 + x_3}, \quad t < 1 - q
\]

\[
\bar{n}_N = \frac{x_1 + nx_2 + x_t}{x_1 + x_2}, \quad t < 1 - q
\]

\[
n_M = \frac{nx_3 - 2x_1}{x_1 + x_3},
\]

\[
n_N = \frac{nx_2 - 2x_1}{x_1 + x_2}
\]

Inequalities 16 and 17 continue to hold.

### 7.2 Additional Data Analysis

#### 7.2.1 Mock-Ups of the Webpage

Due to confidentiality agreements with the website, we are not permitted to reprint the actual webpages concerned. However, to give a basic idea of what they looked like before and during the experiment, we constructed two mock-up webpages in Figures 4.

#### 7.2.2 Data Processing

There are several challenges in processing the data. The first challenge comes from unintentional clicks, due to, for example, slow website response time. Since privacy rules prevented our accessing the IP addresses, we could not identify repeat clicks by the same user. As an alternative strategy, we dropped 60,925 observations where there were multiple requests for the same link.
within the same minute. To check the sensitivity of our results to this procedure, we also tried dropping observations where there were more than five requests for the same link within the same minute. There was no substantial change in our findings.

The second processing challenge was that there was a small amount of vendor entry into and exit from this information portal during the period we study. In the reception hall category, there was one change where a reception hall with a name beginning with “O” was removed during the second month of the experiment and a vendor beginning with “T” was put in its place. This shifted the position of all reception halls with first letters “P” to “S” up one place for the second month of the experiment. The reception halls affected ranked initially between 95 and 114 and subsequently ranked between 93 and 113. In the florists category, there was one change where a florist beginning with “V” was removed in the second month of the experiment. One florist beginning with “W” was affected by this change and moved position from 58 to 57. We have experimented both with incorporating these vendors and excluding these vendors. The results
are almost identical, so we present results for a balanced panel where we exclude the vendors that exited and entered.

### 7.2.3 Industry Level Robustness Investigation

One concern with studying the wedding industry is that any experiments could be confounded by seasonal changes in level of interest in wedding vendors. This is why we have such a rich set of controls to capture changes in cross-category interest over time. Table 6 provides some explanation for the relative stability in clicks over the course of our experiment. This table shows that entry and exit for this industry is more evenly spread across the year than the conventional belief in the prevalence of summer weddings would suggest. The largest monthly shock is in December, when 19 percent of engagements happen. By contrast, there is less variation in how many weddings take place each month. June and July, commonly supposed to be the most popular months for weddings, only account on average for 10.5 percent of the interest in wedding vendors.

It eases the interpretation of the $Displayed_{jt}$ term in Table ?? if caterers (where clicks were not displayed) have similar time-variant demand shocks to the bridal attire category (where clicks were displayed). According to industry experts we asked, the demand for wedding services does vary somewhat with the season, but it is reasonable to believe that various categories are subject to similar levels of seasonal shocks due to the high degree of complementarity across categories for the end product.

Additional confounds could arise if a rival website started providing listings of, for example, urban bridal shops during our field experiments, which would plausibly reduce the visits to urban bridal vendors on the website running our experiment and confound our interpretation of $PrevClicks_{jt} \times Displayed_{jt} \times Niche$. Fortunately, during the time period we study, this website had no significant local competitors in the state it operates in. National competitors, such as “TheKnot.com” and “WeddingChannel.com”, did not change their listing policies.
Table 6: Shifts in Number of Brides Browsing for Vendors

<table>
<thead>
<tr>
<th>Month</th>
<th>Percentage of Engagements</th>
<th>Percentage of Marriages</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>5 %</td>
<td>6 %</td>
</tr>
<tr>
<td>February</td>
<td>8 %</td>
<td>7 %</td>
</tr>
<tr>
<td>March</td>
<td>4 %</td>
<td>7 %</td>
</tr>
<tr>
<td>April</td>
<td>6 %</td>
<td>8 %</td>
</tr>
<tr>
<td>May</td>
<td>6 %</td>
<td>8 %</td>
</tr>
<tr>
<td>June</td>
<td>8 %</td>
<td>11 %</td>
</tr>
<tr>
<td>July</td>
<td>9 %</td>
<td>10 %</td>
</tr>
<tr>
<td>August</td>
<td>9 %</td>
<td>10 %</td>
</tr>
<tr>
<td>September</td>
<td>7 %</td>
<td>10 %</td>
</tr>
<tr>
<td>October</td>
<td>9 %</td>
<td>9 %</td>
</tr>
<tr>
<td>November</td>
<td>9 %</td>
<td>7 %</td>
</tr>
<tr>
<td>December</td>
<td>19 %</td>
<td>7 %</td>
</tr>
</tbody>
</table>

Source: Fairchild Bridal Infobank, American Wedding Study, 2002; National Center for Health Statistics, 2004

Another concern is that vendors could have reacted strategically to the field experiment. We examined the data for evidence of suspicious clicks (or “click-fraud”) but could find no patterns of successive clicks that suggested vendors were artificially boosting their own popularity rankings. Vendor prices are not displayed, so cannot act as an alternative quality signal for website browsers. Vendors, correspondingly, would have no incentive to strategically change their price to manipulate customer observational learning. This feature rules out the price endogeneity problem which would have been a key concern if the experiment had been run on a price-grabber style website.
References


