Consumer Search and the Structure of Personal Networks

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Abstract

We study how consumers’ information search for and purchase of new products are affected by structure of their personal network. We focus on two network characteristics namely homophily and balance, which are expected to moderate information diagnosticity and search discomfort. To address threats to internal validity common in network studies, we conduct a randomized experiment in which we manipulate the similarity of preference among consumers and their network contacts and allow them to search for information about a product from these contacts before deciding to make a purchase. We estimate consumers’ utility function and determine how network antecedents moderate the weight on others’ information. Our findings show that consumers like to gather information from similar others as it is perceived to be more diagnostic than information from dissimilar others. Balance has no direct effect on search. This null effect is due to a combination of higher diagnosticity and greater discomfort of gathering information in imbalanced networks. Overall, search from similar others in an imbalanced network is most likely to converge to purchase. Given the co-occurrence of homophily and balance in naturally occurring personal networks, our results emphasize the tradeoff between the two network antecedents for product purchase.

KEYWORDS: Homophily; Balance; Social Search; Quasi-Bayesian Learning
1. Introduction

Consumers often turn to social contacts for advice before making decisions as mundane as whether a given restaurant is worth going to on a Saturday night or as critical as the appropriateness of a wedding venue. They may gather feedback from a friend with shared interests (or similar preferences) as it seems diagnostic. On occasion, consumers may gather product feedback from multiple peers. If these friends have different points of view, it may lead to a more informed decision but can be cognitively taxing. In this paper, we examine empirically the impact of the similarity of preferences among information seekers and their social sources on the amount of search they engage in, and on subsequent product purchase.

Understanding consumer search behavior has long been an object of theory and empirics (e.g., Brown et al. 2011; De Los Santos et al. 2012; Erdem et al. 2005; Hauser et al. 1993; Honka 2014; Kim et al. 2010; Mehta et al. 2003; Moorthy et al. 1997; Weitzman 1979). Recently, social search, i.e., collecting information from peers, has gained a lot of attention partly due to easy access to data on from such platforms as Facebook and Twitter (Godes et al. 2005; Toubia and Stephen 2013). This emphasis on social search is a resurgence as it has actually been the focus of many classic studies in different research streams (e.g., Brown and Reingen 1987; Feldman and Spencer 1965; Granovetter 1973; Lee 1969; Watts and Strogatz 1998). Collectively, these past studies have considered two key questions of theoretical interest. First, how is search behavior affected by personal networks of information seekers (search antecedents)? Second, how does search behavior impact behavioral outcomes (search consequences). For instance, in labor markets, Granovetter (1973) introduced the concept of “the strength of weak ties” to indicate that people closest to the information seeker may all know each other and thus have the redundant information regarding new job openings. Information about job openings and success in finding
new jobs, therefore, is likely to come from acquaintances. For consumer markets, the seminal work of Lee (1969) on how women find abortionists also noted that the nature of ties matter for how successful a search is. In general, extant work has considered search antecedents associated with novelty of gathered information (e.g., weak ties) and search consequences on top end of the purchase funnel (e.g., a change in the consideration set from awareness of new alternatives).

We focus on consumer search closer to purchase where the primary goal of consumers for seeking feedback is to ascertain product quality and validate their beliefs rather than to become aware of other alternatives (e.g., Erdem et al. 2005). In doing so, we complement past literature and investigate the antecedents and consequences of social search for bottom of the purchase funnel. We propose a theoretical framework based on information diagnosticity and cognitive discomfort to investigate how the structure of personal network impacts consumers’ search and purchase decisions. We focus on two characteristics of personal networks namely homophily and balance, which are expected to moderate the diagnosticity of information of gathered information and cognitive discomfort from search.

Many studies have embraced homophily, the tendency for people to associate with similar others, as the primary mechanism of various consumer behaviors such as the adoption of telecommunication service (Hill et al. 2006), click of online ads (Goel and Goldstein 2014), success of referral programs (Schmitt et al. 2011), adoption of health behavior (Centola 2011), and customer defection of a service (Nitzan and Libai 2011). Given the accruing evidence of the relevance of homophily, work has begun to identify why and how it is at work in different contexts (Currarini et al. 2009; Kossinets and Watts 2009; Wimmer and Lewis 2010; Zeng and Xie 2008). While there is a large body of evidence of homophily along socio-demographic lines, homophily due to similar preferences is more difficult to find evidence for as it pertains to latent attributes (e.g., Aral and
Walker 2012, Hill et al. 2006). Such preference-induced homophily, the focus of our paper, is interesting for marketers as it suggests that targeting friends of early adopters of new products is a viable strategy. Marketers would, however, be remiss to take preference-based homophily for granted. Recent work in an online fitness community suggests that when given an opportunity, people seek others similar to them socio-demographically rather than on preference (Centola and van de Rijt 2014). We assess whether preference-based homophily exists in social search and if so, what the underlying drivers are - is it because people perceive information gathered from similar others as more diagnostic (Brown and Reingen 1987; Feldman and Spencer 1965) or because people find it easier to interact with similar others (McPherson et al. 2001; Price and Feick 1984).

The notion of similarity can be extended from dyads to a network. To develop the latter concept, we appeal to the classic work of Heider (1946) and Cartwright and Harary (1956). Heider noted that a social triad is balanced if the product of each tie’s valence (i.e., positively signed for a liking relationship between two individuals, and negatively signed for dislike) is positive and the pattern of relationships is termed as consistent. Note that balance is defined for closed triads (a triad in which all ties are present) and is related to but conceptually different from network closure, which measures the presence or absence of ties. We broaden the concept of balance to consistency in preferences. Consider Ryan with two friends Jim and Mary and suppose Ryan’s preferences for food are reasonably similar to Jim’s and Mary’s. If Jim’s and Mary’s preferences are similar as well then the pattern of the similarity of preference is consistent, and the triad is balanced. In contrast, if Jim’s and Mary’s preferences are dissimilar then the pattern of the similarity of preference is inconsistent.

\footnote{In some situations, the observed effects of homophily can be opportunity-induced, reflecting the fact that people simply have a greater opportunity to meet with similar others. For instance, if Jim and Mary are doctors and work on the same floor in a hospital, they may have a greater opportunity to meet than would be expected by chance. Such opportunity-based homophily is not a relevant driver for our study as we use data from a randomized experiment.}
and the triad is imbalanced. A network is balanced if all triads are balanced (Cartwright and Harary 1956). While prior work has not considered the link between balance and benefit-cost of search, there is some suggestive evidence. Empirical findings show that exposure to different vantage points increases the diagnosticity of information (Burt 2001; Goethals and Nelson 1973; Orive 1988). As there is a greater opportunity of being exposed to different viewpoints in imbalanced networks, it is likely that diagnosticity of information will be higher. As for perceived cost, people may expend greater cognitive effort to process inconsistent information and also experience cognitive discomfort as well, which is more likely to emerge in imbalanced networks (Harkins and Petty 1981; Heider 1946; Mandler 1982).

While the theoretical impact of homophily and balance on consumers’ search decisions can be posited, providing empirical evidence is actually not straightforward. In social contexts, friends with similar preferences are more likely to spend time together and with each other’s contacts. Such interactions typically lead to balanced networks. The phrase “a friend of my friend is my friend” captures this notion. Distinguishing between the effects of these two network antecedents is still valuable, however, even if they tend to be positively correlated in naturally occurring networks (Aral and Van Alstyne 2011; Granovetter 1973). First, whether network structure matters over and above tie characteristics is a fundamental question in network science. As a result, network scientists are interested in the distinction between intra-dyadic and extra-dyadic network effects. Second, consumers, firms or policy makers seeking to design more effective network structures would like to determine whether tie strength and balance have different effects on motivation versus opportunity to provide valuable information and may be at odds with each other (e.g., Hansen 1999).

In this paper, we adopt an experimental paradigm for theory testing. In the experiment, consumers make purchase decisions for individual music tracks while having access to others’
evaluations. Our approach has several advantages over data from field settings to address threats to internal validity common in network studies (e.g., Aral and Walker 2012; Centola 2011; Narayan et al. 2011; Shalizi and Thomas 2011; Wuyts et al. 2004). First, we manipulate the similarity of preference, which is latent and usually confounded in observational data with opportunity of meeting similar others, interpersonal affect, or frequency of interaction. As this manipulation varies the homophily of ties and whether the network is balanced, we cleanly test our proposed impact on behavior. Second, the experimental design controls for such unobserved confounds as endogenous group formation. Third, the experimental design also controls for alternative social influence mechanisms such as passive learning (from exogenous social information), awareness diffusion, or normative pressure in our study. Fourth, as we manipulate the content and availability of social information, which is difficult to observe in secondary data, we can cleanly test the effect of the similarity of preferences on consumers’ decisions.

We report two sets of analyses namely, model free analyses and the results from a utility-based model with consumer learning. While the former shows the overall effect of network antecedents on behavior, the latter allows us to disentangle whether the observed effects are from the impact on information diagnosticity, discomfort from search or both. The latter model also allows for network antecedents to moderate the weight consumers put on information gathered from different sources. There are three key findings. First, there is clear evidence that consumers prefer to gather information from others with similar preferences. Second, feedback from similar others is perceived as more diagnostic than feedback from dissimilar others even with the same objective strength of association. As a result, search from similar others is more likely to converge to purchase than the same amount of search from dissimilar others. Third, imbalance has no direct effect, neither positive nor negative, on the search amount. Our model-based analysis shows that this null effect is due to a
combination of higher diagnosticity and greater discomfort of information gathered in imbalanced networks. As a result, search in an imbalanced network is more likely to converge to purchase than the same amount of search in a balanced network. Given the co-occurrence of homophily and balance in typical personal networks, our results emphasize the trade off on the level of purchase from the two network antecedents.

The remainder of the paper is organized as follows. In Section 2, we describe the theoretical framework. Section 3 contains the research setting, experimental design and the data description. In Section 4, we show the experimental findings. Section 5 develops a utility-based model for consumers’ decisions in our setting with Section 6 showing the empirical specification. Section 7 contains the results from estimating the model. Section 8 concludes with a discussion of implications for marketing theory and practice.

2. Theoretical Framework and Hypotheses

We develop the theoretical framework and propose specific hypotheses for information diagnosticity and cognitive discomfort through which the social ties of information seekers may impact search.

2.1 Homophily

The diagnosticity of information from a peer depends on the strength of association between an individual’s preferences and that of the peer. If a peer with tastes similar (dissimilar) to those of a focal consumer give positive feedback about a product, then that consumer may infer that he will (will not) like it. Current normative models of consumer learning assume that positive feedback from similar others has equivalent information as negative feedback from dissimilar others. In other words, the feedback from similar and dissimilar others with the same strength of association should be equally diagnostic. On the cost side, prior studies implicitly assume that
there is no difference in the cost of collecting information from similar or dissimilar sources as long as a consumer searches for the same amount (e.g., Hauser et al. 1993; Ratchford et al. 2003).

These normative assumptions are at odds with evidence of homophily in social search (Feldman and Spencer 1965; Brown and Reingen 1987). For instance, Feldman and Spencer (1965) found that a majority of new residents seeking a physician (85%) turned to similar friends for a referral and only a minority (15%) turned to a personal source who was an expert in the medical field. Studies using an observational design have difficulty in identifying whether this tendency to seek information from similar others than dissimilar others is driven by a greater opportunity to meet with similar others (i.e., opportunity-induced homophily) or a purposive contact with similar others (i.e., preference-induced homophily). If the evidence of homophily in the previous studies is driven only by opportunity, then there is little reason to expect that people may find the information from similar others as more diagnostic or may experience less discomfort of search from similar others. In such cases, a normative model would hold. However, clear evidence that preference-induced homophily is present in social search would be inconsistent with a normative specification.

Some prior studies provide insights into the underlying drivers for the impact of homophily on search. One stream of research has focused on whether consumers find information from similar others to be more relevant. For instance, Gilly et al. (1998) show that people pay more attention to the information from similar others than that from dissimilar others. Yaniv et al. (2011) note that consumers find more relevant information from similar others, who tend to share similar product needs, than from dissimilar others. We propose that the perceived greater diagnosticity of information gathered from similar others is a driver of preference-induced homophily. Another stream of research has focused on the discomfort of associating with
dissimilar others, albeit similarity was typically based on socio-demographics (e.g., Pettigrew and Tropp 2006; Stephan and Stephan 1985). We posit that such discomfort will be present even when people gather information from others with dissimilar preferences. Thus, we propose the following:²

**H1a:** For the same amount of search, information collected from similar others will be perceived to be more diagnostic than information collected from dissimilar others.

**H1b:** People incur lower discomfort collecting and processing information from similar than from dissimilar others.

### 2.2 Balance

Heider (1946) defined balance in a social triad based on the consistency of liking or sentimental relationships. He proposed that a triad is balanced (imbalanced) if the product of each of the tie’s valence (i.e., positively signed for a liking relationship between two individuals, and negatively signed for dislike) is positive (negative). Cartwright and Harary (1956) expanded the definition on balance for social networks larger than a triad. Such expansion made the concept applicable to a wider range of situations such as the creation of commonly shared norms and values (Sternberg 1998), and dynamics of network formation (Hummon and Doreian 2003). We broaden the concept of balance to denote the consistency of preferences in a social network, and apply it to social search. We term a network as balanced if the product of the valence of preferences (i.e., positively signed for similar preferences, and negatively signed for dissimilar preferences) in a

² Little empirical research has jointly tested the impact of the two drivers on preference-based homophily. This is not surprising as disentangling whether the factors that are important for search are due to their impact on informational benefit or discomfort requires a formal model. The issue is similar to that of disentangling persuasive and informative effects of advertising by means of a formal model (Ackerberg 2001). We identify the two drivers based on (i) observations on both search and purchase and (ii) a formal model of consumer search and learning. We discuss the identification of the two drivers in detail in the Appendix.
network is positive, and investigate the impact of balance on social search via the diagnosticity of information and cognitive discomfort.

While prior work has not considered the link between balance and informational benefit, there is some suggestive evidence. Past empirical findings show that the exposure to different vantage points increases the diagnosticity of information (Burt 2001; Goethals and Nelson 1973; Orive 1988). As it is more likely to acquire information from different viewpoints in an imbalanced network, we expect that diagnosticity of information will be higher. Furthermore, a normative model of consumer learning would suggest a similar result with the intuition being that the variance of a sum of two random variables is smaller when the correlation between the two random variables is negative than positive.\(^3\) Therefore, we propose:

\[\textit{H2a: For the same amount of search, information collected under an imbalanced network will be more diagnostic than information collected under a balanced network.}\]

Prior research has ignored the impact of balance on the discomfort of search (e.g., Hauser et al. 1993; Ratchford et al. 2003). According to Heider (1946), people tend to feel greater cognitive discomfort and tension when there is inconsistency of liking or affect with others. We posit that people experience greater discomfort even when they are exposed to inconsistent information. Furthermore, discomfort may also stem from greater cognitive effort to process inconsistent information (Harkins and Petty 1981; Mandler 1982). As inconsistent information is more likely in an imbalanced system, we propose the following hypothesis:

\[\textit{H2b: For the same amount of search, information collected under an imbalanced network will be more cognitively discomforting than information collected under a balanced network.}\]

\(^3\) The intuition also applies to modern portfolio theory (Markowitz 1952). For a given level of return, the overall risk (variance) of a portfolio can be reduced by investing in assets with negative correlation because the poor performance of one asset can be offset with the good performance of another. In Appendix, we explain the link between imbalance and higher diagnosticity in more detail.
**H2b: People incur greater discomfort of collecting and processing information under an imbalanced network than a balanced network.**

3. Research Setting and Experimental Design

3.1 Research Setting

To cleanly test how similarity in preferences that consumers have with their sources may impact search, we characterize the research setting based on the following features - (i) the number of information sources, (ii) the relationship between consumers and their contacts, (iii) the decision framework, (iv) quality signals and (v) the type of search decision.

**Number of sources.** We assume that a consumer’s social sources can be categorized into two exogenous groups (groups A and B as noted in Figure 1). As an example, a consumer may have several friends who can be categorized into those he knows from school or from work. Thus, the consumer and his two social groups form a social triad. By taking a triadic perspective, we cleanly test the impact of intra-dyadic and extra-dyadic effects. Our test of theory is in line with past work suggesting that many extra-dyadic effects can be explored by moving from dyads to triads and that further expansion to four or more actors does not fundamentally alter the issues (e.g., Wuyts et al. 2004).

**The relationship between the consumer and his contacts.** We assume that a consumer has a mature relationship with both social groups and so knows the similarity of preferences in the social triad. Figure 1 shows an example of a triad where the focal consumer and two social groups form the nodes and the link among any two nodes denotes the similarity of preference between them. In the figure, \(a\) \((b)\) denotes the similarity of preference between a consumer and group A \((\text{group B})\), and \(c\) denotes the similarity of preference between the two social groups. We operationalize the similarity measure as correlation: the value gets closer to 1 \((-1)\) as the positive
(negative) association of preference between two nodes gets stronger. There is no association of preference between two nodes when the similarity measure between them is 0.

Figure 1. The Similarity of Preference in a Social Triad

We denote that a social system is balanced if the product of the valence of preferences is positive - the triad is balanced when $abc > 0$, and imbalanced when $abc < 0$. Under balance (imbalance), the pattern of the similarity of preference is consistent (inconsistent) with each other. For instance, if a focal consumer has a similar preference with the two social groups ($a>0$ and $b>0$) and both groups also have similar preferences ($c>0$), a triad has a balanced preference ($abc > 0$). If, however, a focal consumer has a similar preference with similar preference with the two social groups ($a>0$ and $b>0$) but both groups have dissimilar preferences ($c<0$), a triad has an imbalanced preference ($abc < 0$).

As noted earlier, naturally occurring personal networks contain homophilous ties and are likely to be balanced (Granovetter 1973). Our experiment can disentangle the separate effect of each network antecedent on behavior. Our research setting also reflects the observation that if one focuses on preference in a specific category e.g., music, movies or fashion, many heterophilous ties and imbalanced social networks may be present. For instance, friends may share a similar world view, but may differ in their music preference.
**Decision framework.** A consumer has to make a *purchase* decision, which is whether to purchase a specific product. Before doing so, he may collect evaluations from his contacts. Each evaluation is a quality signal. A consumer decides on the number of signals to collect from each group. We call this his *search* decision. As summarized in Figure 2, we focus on the scenario where a consumer makes a search decision, processes the information acquired from search, and finally makes a purchase decision. We use this framework as a motivation for the formal model described in Section 5.

![Figure 2 Decision Framework](image)

We posit that respondents make their search decision based on their belief about how informative the signals would be and how much discomfort they would experience (e.g., Erdem et al. 2005; Hauser et al. 1993; Ratchford et al. 2003; Seiler 2013). Respondents make their purchase decision after gathering signals. The purchase decision is affected by how informative the collected signals are. However, the discomfort of search (which respondents have already experienced) does not affect the purchase decision directly – it does so only indirectly through the search amount.

**Quality signals.** It is likely that the nature of ties that information seekers have with their contacts impact the latters’ willingness to share information and their trustworthiness (Coleman...
1988; Granovetter 1973; Uzzi 1996, 1997). For instance, ties with contacts having similar preferences may be more intimate and the gathered evaluations more trustworthy (Coleman 1988). In our experiment, we address these confounds by noting that all information providers are willing to share their feedback and are honest in their evaluations regardless of the nature of ties.

Type of search decision. As we wish to investigate how the similarity in preferences between information seekers and sources impact the decision to search, consumers would ideally make the search decision before observing any quality signals. Thus, we impose that respondents perform a simultaneous search (or fixed sample search) about a specific product.4

3.2 Experimental Design
Our design is a novel incentive compatible stated choice experiment in which we control for potential confounds typically found in observational contexts. Our experiment has two phases: Phase 1 involves a calibration task and Phase 2 an incentive compatible choice task. Each phase is described below.

In Phase 1, participants listen to 10 songs of different music genres and rate each song on a 0-10 scale. Participants are told to rate each song carefully as their ratings will be used in matching them with other participants in the second phase of the experiment.

In Phase 2, respondents make a purchase decision for 18 unidentified songs (no artist or genre was specified) without listening to them. We did not identify the songs to isolate the causal impact of preference similarity on search. Participants know that songs are worth $1.25 on iTunes. For each song, a purchase decision for participants means deciding between receiving

4 De los Santos et al. (2012) estimated both simultaneous and sequential search models in the context of online search for experiential products, which is also the setting in our experiment, and found that a simultaneous search model fit the data better.
the unidentified song digitally or $1 cash (in addition to participation fee). For instance, participants can decide to purchase each one of those 18 songs or not purchase any one of them. Participants’ decisions are incentive aligned as they are told that one out of all 18 unidentified songs will be randomly picked at the end of the survey, and they will be compensated with either the actual song (if they had chosen to purchase it) or $1 additional cash.

Each song is described by six attributes. The first two attributes gives a summary of aggregate evaluations for the song - (#1) the average of the song’s rating \( R_{ij}^{0M} \) from iTunes on a 0-10 scale and (#2) the standard deviation \( \tau_j^M \) which captures the population heterogeneity in song evaluations. The superscript \( M \) denotes manipulated attributes. The average of aggregate evaluation has three levels: low (0.5-3.0), medium (3.0-7.0) and high (7.0-9.5). A respondent sees a randomly chosen value in the range corresponding to a level. The standard deviation of aggregate evaluations has three levels (0.5-1.5, 1.5-3.5, 3.5-4.5), and the respondent sees an actual value randomly chosen within a range corresponding to a given level.

In each profile, participants also have access to social information before they make a purchase decision. Respondents are told that 200 Undergraduates and 200 MBAs have previously listened to the same 10 songs as they did in Phase 1 and also the 18 unidentified songs that they will be making purchase decisions for. They are then told that genre-specific similarity of preference measures in the triad have been computed based on their evaluations of the 10 songs in Phase 1. We explain that the similarity measures are constructed by comparing the respondents’ ratings with the \textit{average} rating within each group. Respondents are provided with information on three more song attributes: (#3) similarity in preference between the participant and undergraduates \( a_j^M \), (#4) similarity between the participant and MBAs \( b_j^M \), and (#5)
similarity between undergraduates and MBAs ($c_j^M$). We manipulate all three measures for each song (as the superscript indicates). The absolute similarity between the participant and Undergraduates as well as the participant and MBAs has three levels each (0.1-0.3, 0.3-0.7, 0.7-0.9). A respondent sees a similarity measure for each source which has an absolute value randomly chosen within a range corresponding to a given level, and a sign randomly chosen to be positive or negative (representing similar or dissimilar preference). The similarity in preference between MBAs and Undergraduates ($c_j^M$) is randomly chosen within a range where the covariance of triadic similarity satisfies typical regularity conditions.

Finally, (#6) the standard deviation of evaluations within the two social groups ($\sigma_j^M$) captures within-group heterogeneity in evaluations. It is set to be equal across the two groups, and fixed to be one-half of the standard deviation of the aggregate evaluations. We do not manipulate it independently to reduce the complexity of the problem for respondents.\(^5\) We generate two orthogonal designs of 18 profiles (unidentified songs) and each participant in the study is assigned to one of the two designs.

For each unidentified song, respondents first make the search decision. Based on the aggregate evaluations of the song and preference similarity measures, they decide on how many

\(^5\) In a pilot study with a convenience sample of 10 students, we found that it was difficult for them to understand all the information in a profile where we had different standard deviations for each of the two social groups. As our primary goal is to test how homophily and balance impact consumers search, the lack of manipulation of the within-group heterogeneity should have little impact.
Figure 3. Screenshot of Survey Interface

(a) Search decision interface

"Song 3"
We want you to predict (1) how much you will like a new song and (2) whether you would like to purchase the song.

You decide on how many people you want to reach out to in each group. You can reach out to as many people as you want in each group. Recall that more people you choose to reach out to in each group, the more certain you will be about that group's rating of the song. If you do not want to reach out to anyone in a specific group, your answer should be 0 for that group.

To retrieve each rating from our database, it will take half a second. You can move to the next question only after all the ratings are successfully retrieved.

1) How many undergrads will you contact?
2) How many MBAs will you contact?

(b) Purchase decision interface

All rating data are successfully retrieved. As a result of your information search, you got the following results:
- The average rating among 2 undergrads whom you reached out to is 6.0.
- The average rating among 3 MBAs whom you reached out to is 5.4.

The figure below replicates the information we presented in the previous page:

3) Would you like to purchase the song?
   - Yes
   - No
individual evaluations (i.e., quality signals) to acquire from each social group. As each group consists of 200 participants, the maximum number of signals that one can acquire from each group is 200. To ensure that the respondents take the search task seriously, we indicate that they have to wait for half a second to retrieve a quality signal.\(^6\) Figure 3a shows an example of the search decision interface. After completing the search decision, respondents move to the purchase decision (Figure 3b for the interface). Respondents are provided with the average rating of randomly sampled individuals from each social group with the sample size based on their search decision. In Figure 3a, for example, a respondent decides to collect 2 (3) signals from undergraduates (MBAs). He is told that the average rating among the 2 undergraduates (3 MBAs) is 6.0 (5.4). We manipulate the quality signals that respondents see. After observing the signals from each group, respondents make their purchase decision. This completes the task for one song, and respondents go through the same task for 18 songs.

4. Data and Analysis

4.1 Data

The data contains 2,736 \(=152 \text{ subjects} \times 18 \text{ profiles}\) pairs of search (how many signals to acquire) and purchase decisions (whether or not to purchase a song). Table 1 provides the summary statistics of search and purchase decisions. The average total search amount is around 20 signals per song. In 33\% of observations, respondents choose to purchase a song, and 88\% of them purchase at least one song.

\(^6\) In the Appendix, we show that our main results are qualitatively robust to a different level of wait time.
Table 1. Summary Statistics of Search and Purchase Decision

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<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>2.5%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Amount of Search</td>
<td>19.2</td>
<td>32.2</td>
<td>0</td>
<td>5</td>
<td>10</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>Purchase Decision (0 is no purchase; 1 is purchase)</td>
<td>0.33</td>
<td>0.47</td>
<td></td>
<td></td>
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Figure 4a summarizes the relationship between the similarity of preferences and (logarithm of) the total amount of search (after adding 1 to avoid the log(0) problem) in the raw data.\(^7\) On average, the search amount is greater when there are greater number of others with similar preferences \((p<0.05)\), but is not significantly different between balanced and imbalanced triads \((p=0.28)\). Figure 4b summarizes the relationship between the similarity of preferences and the purchase rate. On average, the purchase rate is greater when there are greater number of others with similar preferences \((p<0.001)\), but is not different between balanced and imbalanced triads \((p=0.19)\). The figures suggest that consumer search and purchase decisions are sensitive to the similarity of preferences between an information seeker and their peers, but the results could have been driven by other confounds. For instance, purchase rate could have been driven by signals that respondents actually observed and how much they search. Likewise, respondents could experience fatigue as they go through the study and this can impact the total search amount. To better understand how the similarity of preferences affect consumer search and purchase decision, potential confounds need to be controlled for. Next, we do so using a regression analysis.

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\(^7\) As shown in Table 1, the distribution of total search amount is right-skewed. To prevent our results being driven by outliers, we use log transformation of total search amount for Figure 4a.
4.2 Findings from the Experimental Data

We estimate a regression model of the logarithm of total amount of search using covariates such as the number of sources with preferences that are dissimilar to those of the information seeker (which takes a value of 0, 1, or 2 for a profile), an indicator for whether the social triad is imbalanced, the mean and standard deviation of aggregate evaluations, and (logarithm of) the order in which the song is presented (which takes a value of 1, 2, … 18). The latter is included to control for respondents’ fatigue as they go through the study. The unit of analysis is a subject-song observation, with 2,736 (=152 subjects × 18 song profiles) observations, and we include a subject-specific random intercept to control individual heterogeneity. Table 2 shows the results.

The total search amount decreases with the number of sources with dissimilar preferences ($p<0.001$). While this finding provides evidence for preference homophily in the amount of search, it is not possible to disentangle if this is due to lower diagnosticity of information from dissimilar others ($H1a$) or the higher discomfort of search ($H1b$). Interestingly, imbalance has a null effect on the search amount ($p = 0.57$), which may be consistent with both hypotheses.
regarding imbalance – if people find the information more diagnostic under imbalance (H2a) but have greater discomfort from search (H2b), the two effects may cancel each other. Effects of other control variables are not of interest per se, but provide face validity for the experiment: the amount of search increased with the average and variance of aggregate evaluations ($p < 0.001$, $p < 0.05$ respectively).

Table 2. Drivers for Search Decision

<table>
<thead>
<tr>
<th></th>
<th>Est (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.01 (0.09)**</td>
</tr>
<tr>
<td>Number of Dissimilar Sources</td>
<td>-0.12 (0.03)**</td>
</tr>
<tr>
<td>Imbalance</td>
<td>0.03 (0.04)</td>
</tr>
<tr>
<td>Mean of Aggregate Evaluation</td>
<td>0.05 (0.01)**</td>
</tr>
<tr>
<td>SD of Aggregate Evaluation</td>
<td>0.06 (0.02)**</td>
</tr>
<tr>
<td>Log(Order of song)</td>
<td>-0.29 (0.02)**</td>
</tr>
</tbody>
</table>

Note: * $p \leq 0.05$, ** $p \leq 0.01$. Standard errors in parentheses

To understand how the purchase decision is driven by the factors of interest, we estimate a binary probit model of purchase incidence. The covariates include the number of sources with preferences that are dissimilar to the information seeker, imbalance indicator of the triad, mean and standard deviation of aggregate evaluations, (logarithm of) search amount and the content of social information. We operationalize the content of social information as the weighted sum of the observed average rating from each group where the weights are (logarithm of) the number of contacts from each group.8 We also include the interactions of social information content with the number of dissimilar sources and the indicator of structural imbalance. As the unit of analysis is subject-song observation, we have 2,736 (=152 subjects × 18 song profiles) observations, and we include a subject-specific random intercept to control individual heterogeneity. Table 3 shows the results.

8 We also fit a model where social information content was operationalized as the average of the observed average rating from each group (i.e., weighted sum of the observed average rating from each group where the weight is 1/2 each). The findings in Table 3 remain robust.
Table 3. Drivers of Purchase Decision

<table>
<thead>
<tr>
<th></th>
<th>Est (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-1.63 (0.21)**</td>
</tr>
<tr>
<td>Number of Dissimilar Sources</td>
<td>-0.06 (0.09)</td>
</tr>
<tr>
<td>Imbalance</td>
<td>0.03 (0.12)</td>
</tr>
<tr>
<td>Mean of Aggregate Evaluation</td>
<td>0.47 (0.02)**</td>
</tr>
<tr>
<td>SD of Aggregate Evaluation</td>
<td>0.24 (0.05)**</td>
</tr>
<tr>
<td>Log(Search Amount+1)</td>
<td>-0.12 (0.06)*</td>
</tr>
<tr>
<td>Social Information Content</td>
<td>0.12 (0.01)**</td>
</tr>
<tr>
<td>Social Information Content × Number of Dissimilar Sources</td>
<td>-0.10 (0.02)**</td>
</tr>
<tr>
<td>Social Information Content × Imbalance</td>
<td>0.16 (0.02)**</td>
</tr>
</tbody>
</table>

Note: * $p \leq 0.05$, ** $p \leq 0.01$. Standard errors in parentheses.

The results show that the probability of purchase increased with the search amount ($p<0.05$) and with favorable social information ($p<0.001$). The number of dissimilar sources ($p=0.61$) and imbalance ($p=0.83$) do not directly impact the purchase rate when the content of social information is zero. Consistent with $H1a$, people tend to be less affected by social information when there are a greater number of dissimilar others ($p<0.001$) and discount the diagnosticity of information from dissimilar others. Consistent with $H2a$, people are more affected by social information collected under an imbalanced system ($p<0.001$). This result sheds further light on the null effect of imbalance on the amount of search (See Table 2). Given the higher benefit from information gathered in an imbalanced system, people should search more. As this was not the case, we can infer that it may have been due to a greater discomfort from search ($H2b$). This is clearly only an indirect way to support $H2b$ and we do it more formally using a utility-based model in the next section. Coefficients of other control variables provide face validity. People are more likely to purchase a song when they collect more signals ($p<0.001$), the average aggregate rating is greater ($p<0.001$), and the variation of aggregate rating is greater ($p<0.001$). $^9$ In

$^9$ The latter result is surprising but may stem from confounds, e.g., search endogeneity. We address the problem by means of a formal model in Section 6.
Appendix, we show that the results of the simple analyses on search and purchase are robust to a different level of wait time.

Although the above regressions control for potential confounds to test the relationship between the similarity of preferences and consumer decisions, the analyses still suffer from two key limitations. First, it is not possible to disentangle whether the attributes that affect the amount of search are due to either their impact on diagnosticity, discomfort from search or both. Second, the endogenous relationship between search and purchase decisions is not accounted for. It is likely that consumers make a decision to search based on their expectations of the later purchase decision. We address both these limitations by developing a formal utility-based model of consumer search and purchase decisions combined with a model of consumer learning.

5. Utility-based Modeling Framework

We develop a formal model for decisions that consumers make in the stated-choice experiment. For each song, a consumer makes two interconnected, but temporally separated decisions. In stage 1 ($t_1$), consumers decide how many quality signals to acquire from other consumers (“search decision”). In stage 2 ($t_2$), they decide whether to purchase the song (“purchase decision”). Between the two stages, consumers use the information they have collected to update their beliefs about the song (“consumer learning”).

5.1 Utility Specification

We assume that consumers are utility maximizers and that the search and purchase decisions are driven by the same utility function. Let $I_i(t)$ denote the information set of consumer $i$ at time $t$. For notational simplicity, we omit the song subscript $j$ in the information set. The information set at a particular time characterizes the state of the consumer and includes all known factors that
affect current utility at time $t$ and any future utilities. In our setting, there are two time points, $t_1$ and $t_2$, and a consumer has a different information set at these two time points.

We define a consumer $i$'s indirect utility from purchasing song $j$ at time $t$ using a constant absolute risk aversion (CARA) specification (e.g., Narayanan and Manchanda 2009; Zhao et al. 2013):

$$U_{ij}(I_i(t)) = \alpha_i - \exp\left(-\beta_i R_{ij}^E(I_i(t))\right) + \varepsilon_{ij}(I_i(t)), \quad t = t_1 \text{ or } t_2. \tag{1}$$

The term $R_{ij}^E$ refers to consumer $i$'s rating (or evaluation) of song $j$ and is realized only after product experience. We use the term $R_{ij}^E(I_i(t))$ to denote explicitly that consumer $i$'s knowledge about $R_{ij}^E$ at time $t$ depends on his information set $I_i(t)$. The parameter $\alpha_i$ captures the baseline utility of purchasing a song, and the parameter $\beta_i$ captures the effect of song evaluation on purchase utility. The error term $\varepsilon_{ij}(I_i(t))$ is also dependent on the information set. The error term is stochastic to consumers at the time of search (Stage 1), but is observable at the time of purchase (Stage 2). This assumption parsimoniously captures the temporal separation between the search and purchase decisions. Finally, the utility from not purchasing the song is set to 0.

5.2 Stage 1: Search Decision

We first discuss how a consumer makes the purchase decision after conducting a specific amount of search. This clarifies the link between search and its impact on purchase. Next, we specify the beliefs that consumers hold for stochastic variables at the time of search. Finally, we describe how consumers determine their optimal level of search given these beliefs.

---

10 Recall that we did not provide attributes of the songs (e.g., genre, artist, etc) to isolate the impact of preference similarity on consumer search decisions.
**Link between search and purchase.** Suppose consumer $i$ collects $n_{ij} = (n_{ij}^A, n_{ij}^B)$ signals from the two groups and the average of these collected signals is $\bar{x}_{ij} = (\bar{x}_{ij}^A, \bar{x}_{ij}^B)$. After this search, consumer $i$’s information set at time $t_2$, $I_i(t_2)$, includes $n_{ij}$ and $\bar{x}_{ij}$. Let $f_i^{RE}(R_{ij}^E | I_i(t_2))$ denote consumer $i$’s belief about his own evaluation given this information set.

As consumer $i$ is uncertain about his own song evaluation, he will determine the expected utility of purchasing song $j$ with respect to his beliefs about the song. Consumer $i$ will purchase song $j$ if and only if it provides higher expected utility than not purchasing it. Equivalently, consumer $i$ will purchase song $j$ if:

$$E_{R_i^{E}(I_i(t_2))} [U_{ij}(I_i(t_2))]>0,$$  

(2)

where $E[.]$ is the expectation operator. Using the expression in Equation (1), the term $E_{R_i^{E}(I_i(t_2))} [U_{ij}(I_i(t_2))]$ can be expressed as:

$$E_{R_i^{E}(I_i(t_2))} [U_{ij}(I_i(t_2))] = E_{R_i^{E}(I_i(t_2))} [\alpha_i - \exp(-\beta_i R_{ij}^E(I_i(t_2))) + \varepsilon_{ij}(I_i(t_2))],$$  

(3)

where $u_{ij}(I_i(t_2))$ denotes the systematic component of the expected utility of purchase. Note that the stochastic component of utility, $\varepsilon_{ij}$, is observable to consumers at Stage 2.

The above description emphasizes that a consumer’s decision of whether or not to purchase a song depends on his earlier search decision as the number and the content of signals ($n_{ij}$ and $\bar{x}_{ij}$) alter his information set at the time of purchase.

**Initial beliefs.** We elaborate on consumers’ beliefs about the relevant stochastic variables given the search decision, $n_{ij}$, and the information set at the search stage, $I(t_i)$. We specify
beliefs that consumers hold about (1) own evaluation prior to search, \( R^E_y(I(t_i)) \), (2) signals to be observed, \( \overline{R}_y(I(t_i),n_y) \), and (3) random component of utility, \( \epsilon_y(I(t_i)) \).

Consumer \( i \) is uncertain about his own evaluation \( (R^E_y) \) for a song \( j \). Likewise, we assume that he is also uncertain about the average evaluations in the two social groups \( (\overline{R}^A_y, \overline{R}^B_y) \). Uncertain beliefs that a consumer has about vector \( R_y = (R^E_y, \overline{R}^A_y, \overline{R}^B_y) \) is represented by the distribution, \( f^R_i(R_y | I_i(t_i)) \).

As explained earlier, a consumer knows the aggregate distribution of song evaluation when he makes a search decision \( (t_i) \). As a respondent’s evaluation is a sample from the population distribution of song evaluation, his prior belief about his evaluation \( (R^E_y) \) is represented by the aggregate distribution which is normally distributed with mean \( R^0_y \) and variance \( \tau^2_y \). A consumer also knows the size of the two social groups \( (N_y = (N^A_y, N^B_y)) \), so the average of any signals gathered from the two social groups \( (\overline{R}^A_y, \overline{R}^B_y) \) are drawn from the distribution with mean \( R^0_y \) and variance \( (\tau^2_y/N^A_y, \tau^2_y/N^B_y) \) respectively.

We assume that the consumer knows the similarity of preference in the social triad, \( \rho_y = (a_y, b_y, c_y) \) – how similar (or dissimilar) his preferences are to those of each social group \((a_y, b_y)\), and how similar (or dissimilar) the preferences of the two social groups are \((c_y)\).

Therefore, a consumer believes that the vector \( R_y \) is a multivariate sample from the population distribution. With the normality assumption, we can express \( f^R_i(R_y | I_i(t_i)) \) as:
Given Equation 4, a consumer $i$'s initial belief about his own rating, $f_t^{RE}(R_{ij} | I_i(t_i))$, is obtained from the marginal distribution:

$$f_t^{RE}(R_{ij} | I_i(t_i)) = N(R_{ij}^0, \tau_{ij}^2).$$

A consumer believes that a signal from group A or B is i.i.d. normal with an unknown average evaluation ($R_{ij}^A(I_i(t_i))$ or $R_{ij}^B(I_i(t_i))$) and standard deviation ($\sigma_{ij}^A$ or $\sigma_{ij}^B$). With these assumptions, the belief about the sample average of $n_{ij} = (n_{ij}^A, n_{ij}^B)$ signals, $f_t^\tau(\bar{\epsilon}_{ij} | I_i(t_i), n_{ij})$, is:

$$f_t^\tau(\bar{\epsilon}_{ij} | I_i(t_i), n_{ij}) = N\left(\bar{\epsilon}_{ij}^0, \tau_{ij}^2\right),$$

where the expression is obtained by combining the uncertainty about the average among collected signals from each group and the uncertainty about average evaluation in each group.

The utility error is stochastic from consumers’ perspective in the search stage. A consumer believes that utility error is normally distributed with mean 0 and unit variance, i.e.,

$$f_t^\epsilon(\epsilon_{ij} | I_i(t_i)) = N(0,1).$$

**Optimal search.** For consumer $i$, let $k_{ij}^A$ and $k_{ij}^B$ denote the *perceived* cost of search for obtaining a quality signal from the social groups A and B, respectively. We allow the perceived cost to differ to test whether the cognitive discomfort of collecting and processing a signal from each group differs (Heider 1946).
Given the information set of consumer $i$ at $t_1$, $I_i(t_1)$, the utility from search $U^S_{ij}(\cdot)$ for a specific amount of search $n_{ij}$ is as follows.

$$U^S_{ij}(I_i(t_1), n_{ij}) = \begin{cases} U_{ij}(I_i(t_2) \mid I_i(t_1), n_{ij}) - k^A_{ij}n^A_{ij} - k^B_{ij}n^B_{ij} + \xi_{n_{ij}}, & \text{when song } j \text{ is purchased}, \\ -k^A_{ij}n^A_{ij} - k^B_{ij}n^B_{ij} + \xi_{n_{ij}}, & \text{when song } j \text{ is not purchased}. \end{cases} \quad (7)$$

Here the term $\xi_{n_{ij}}$ is known to the consumer and can be interpreted as a fixed cost of gathering $n_{ij}$ signals (De los Santos et al. 2012). We use the term $U_{ij}(I_i(t_2) \mid I_i(t_1), n_{ij})$ to denote explicitly that the consumer $i$'s utility is based on how his information set at $t_2$ will change due to his information at $t_1$ and the amount of search he decides to engage in. The term contains two key components that are uncertain to consumers at time $t_1$. First, the utility error is stochastic, and consumer believes that it follows $f^e_i(\epsilon_{ij} \mid I_i(t_1))$. Second, the consumer is yet to observe any signals, and his uncertain belief follows $f^S_i(\tilde{s}_{ij} \mid I_i(t_1), n_{ij})$. The latter is important as it indicates that a consumer does not know what belief he will hold about his own song evaluation, $f^R_i(R^E_{ij} \mid I(t_2))$, at the time of purchase. Due to both uncertain components, the consumer does not know whether he will purchase the song or not.

Thus, a consumer $i$'s expected utility from search for song $j$'s evaluations is:

$$E[U^S_{ij}(I_i(t_1), n_{ij})] = E_{I_i(t_2) \mid I_i(t_1)} \left[ 1_{I_i(t_2)} \times E_{R^E_{ij}(I(t_2))} \left[ U_{ij}(I_i(t_2) \mid I_i(t_1), n_{ij}) \right] \right] - k^A_{ij}n^A_{ij} - k^B_{ij}n^B_{ij} + \xi_{n_{ij}}, \quad (8)$$

where $1_{I_i(t_2)}$ is an indicator which is 1 if a consumer $i$ purchases a song $j$, and 0 otherwise. The above equation implies that expected search utility for a consumer equals the expected purchase utility (with respect to uncertain belief about own evaluation after search) after integrating over
all possible \( I(t_2) \) he may have given \( I(t_1) \). Given Equations 2 and 3, we can rewrite Equation 8 as a function of \( u_{ij}(I(t_2)) \) and \( \varepsilon_{ij}(I(t_2)) \).

\[
E[U^S_{ij}(I(t_1), n_{ij})] = E_{t_i(t_2)} \left[ \left( u_{ij}(I(t_2)) + \varepsilon_{ij}(I(t_2)) \right) \right] - k_{ij} n_{ij}^A - k_{ij} n_{ij}^B + \xi_{n_{ij}}, \tag{9}
\]

We assume that the consumer evaluates the expected utility associated with each level of search. He then chooses the level \( n_{ij}^* \) that maximizes the expected utility from search. Given the size of each group \( (N_{ij}) \), the consumer cannot contact more than \( N_{ij}^A (N_{ij}^B) \) number of people from each group. Thus,

\[
n_{ij}^* = \arg \max_{n_{ij}} E[U^S_{ij}(I(t_1), n_{ij})], \text{ where } 0 \leq n_{ij}^{A*} \leq N_{ij}^A \text{ and } 0 \leq n_{ij}^{B*} \leq N_{ij}^B. \tag{10}
\]

### 5.2 Consumer Learning (Between Stage 1 and Stage 2)

After collecting signals from each group, consumers update their belief about not only their own song evaluation \( (R_{ij}^E) \) but also the average evaluations in the two social groups \( (\bar{R}_{ij}^A, \bar{R}_{ij}^B) \). We assume that consumers update their beliefs about all evaluations according to Bayes rule. Given the prior and the signal distribution specified in the previous section, the learning process follows standard Bayesian learning. As a result, we obtain the posterior belief about all three evaluations, \( f_{ij}^R(R_y | I_i(t_2)) \), which follows a multivariate normal distribution and the posterior mean and variance is a function of the similarity of preference in the social triad, \( \rho_{ij} = (a_{ij}, b_{ij}, c_{ij}) \). The specification of the posterior distribution of vector \( R_{ij} \) is available upon request. In Section 6, we distinguish between two learning models, both of which have Bayesian updating mechanism laid
out here but differ on whether update is based on the objectively manipulated attributes or subjectively perceived ones.

### 5.3 Stage 2: Purchase Decision

In the purchase stage, a consumer determines whether or not to purchase the song. Given consumer’s beliefs about their own evaluation at the time of purchase, the expected utility from purchasing song \( j \) is:

\[
E_{R_E(i(t_2))}[U_y(I_i(t_2))] = \alpha_i - \exp\left(-\beta_i PM_{ij}(n_{ij}, \bar{x}_{ij}) + \frac{\beta^2_i}{2} PV(n_{ij})\right) + \epsilon_y(I_i(t_2)),
\]

where \( PM_{ij}(n_{ij}, \bar{x}_{ij}) \) denotes posterior mean and \( PV(n_{ij}) \) denotes posterior variance about own song evaluation \( (R^E_{ij}) \). See Appendix for the expression of posterior mean and variance.

Note that the utility error is known to a consumer when a purchase decision is made. A consumer purchases the song when its expected utility is higher than not purchasing it.

### 6. Empirical Specification of Two Consumer Learning Models

We propose two specifications for how consumers learn in our setting. Table 4 summarizes both model specifications.

Objective learning (OL) model is the baseline model where people update the belief about their own product evaluation according to Bayes rule applied to the objective (manipulated) values of all six attributes \( (R^{OM}_j, \tau^M_j, a^M_j, b^M_j, c^M_j, \text{ and } \sigma^M_j) \). The OL model has two key limitations for testing how consumers weigh information gathered from different sources. First, the diagnosticity of feedback is determined by the strength of association (\( |a^M_j| \) or \( |b^M_j| \)), and the informational benefit from similar and dissimilar sources with the same strength of association is
forced to be identical. Thus, positive feedback from similar others and negative feedback from dissimilar others are equivalent. Therefore, we cannot test whether consumers perceive information gathered from similar others as more diagnostic or not (H1a). Second, the diagnosticity of information is always greater in an imbalanced network \( (a_j^M b_j^M c_j^M < 0) \) than a balanced one \( (a_j^M b_j^M c_j^M > 0) \). The absolute similarity between sources cancels the noise of quality signals under an imbalanced network but amplifies it under a balanced network, so informational diagnosticity is always greater in the former. Therefore, we cannot test whether people deem the information under imbalance to be more diagnostic or not (H2a). Please see Appendix for a broader discussion of these two limitations.

Table 4. OL vs. SL Specification

(a) Related to Informational Benefit (\( \Theta_j \))

<table>
<thead>
<tr>
<th>Attributes</th>
<th>OL Specification</th>
<th>SL Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Similarity with Groups ( (a_j, b_j) )</td>
<td>( a_{ij} = a_j^M ) and ( b_{ij} = b_j^M )</td>
<td>( a_{ij} = a_j^M \times \exp(\theta_0 + \theta_0^{imb} + \theta_0^{neg} \delta_j) ), ( b_{ij} = b_j^M \times \exp(\theta_0 + \theta_0^{imb} + \theta_0^{neg} \delta_j) ).</td>
</tr>
<tr>
<td>Similarity b/w Groups ( (c_j) )</td>
<td>( c_{ij} = c_j^M )</td>
<td>( c_{ij} = c_j^M \times (\theta_0^{imb} + \theta_0^{imb} \delta_j) )</td>
</tr>
<tr>
<td>Aggregate Mean ( (R^0) )</td>
<td>( R_{ij}^0 = R_{ij}^{0M} )</td>
<td>( R_{ij}^0 = R_{ij}^{0M} )</td>
</tr>
<tr>
<td>Aggregate Variation ( (\tau_j) )</td>
<td>( \tau_{ij} = \tau_j^M )</td>
<td>( \tau_{ij} = \tau_j^M \times \exp(\theta_0) )</td>
</tr>
<tr>
<td>Within-Group Variation ( (\sigma_{ij}^\alpha, \sigma_{ij}^\beta) )</td>
<td>( \sigma_{ij}^\alpha = \sigma_{ij}^\beta = \sigma_j^M )</td>
<td>( \sigma_{ij}^\alpha = \sigma_{ij}^\beta = \sigma_j^M \times \exp(\theta_0^{imb}) )</td>
</tr>
</tbody>
</table>

(b) Related to Perceived Cost of Search (\( \Delta_j \))

<table>
<thead>
<tr>
<th>Attributes</th>
<th>OL Specification</th>
<th>SL Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Cost ( (k_{ij}^\alpha, k_{ij}^\beta) )</td>
<td>( k_{ij}^\alpha = k_{ij}^\beta = \exp(\delta_{\alpha} + \delta_j \delta_{\alpha} \delta_{imb}) )</td>
<td>( k_{ij}^\alpha = \exp(\delta_{\alpha} + \delta_j \delta_{\alpha} \delta_{imb}) ), ( k_{ij}^\beta = \exp(\delta_{\alpha} + \delta_j \delta_{\alpha} \delta_{imb}) )</td>
</tr>
</tbody>
</table>

To test our hypotheses, we propose a quasi-Bayesian learning model, which we term as the
subjective learning (SL) model. It maintains the assumption that consumers update using Bayes’ rule but rely on subjectively revised attributes for doing so (e.g., Camacho et al. 2011). In particular, we specify that the subjectively perceived value of attributes depend on the two network antecedents of central interest. The additional step of allowing for subjective interpretation by consumers provides substantial model flexibility. In Table 4a, let \( \Theta_i \) denote the vector of all individual-level parameters related to informational diagnosticity from others’ evaluations in the SL specification.

First, to assess the impact of homophily on information diagnosticity (H1a), we specify that the subjective strength of association that respondents have with their sources is moderated by the valence of preferences with each group. We define two binary variables \( \text{neg}_A^j \) and \( \text{neg}_B^j \), which take a value of 1 when a respondent has dissimilar preferences with Group A or Group B, respectively, and is 0 otherwise. We use the two variables to relate the subjective similarity of the information seeker with each source \((a_{ij}, b_{ij})\) to the manipulated similarity \((a^M_j, b^M_j)\) with parameters \( (\theta^{01}_i, \theta^{\text{with}}_i) \) determining the ratio of subjective to manipulated similarity.\(^{11}\) A negative \( \theta^{\text{with}}_i \) indicates that consumer \( i \) subjectively discounts the strength of relationship with dissimilar others compared to that with similar others. In this case, consumer \( i \) perceives the information from dissimilar others is less diagnostic (H1a).

Second, to test consumers’ attitude towards balance (H2a), the perceived relationship between the sources is moderated by the balance status in the social system \((\text{imb}_j \text{ is 1 if the relationship is imbalanced and is 0 for balance})\). Subjective similarity between the groups \((c_{ij})\) is

\(^{11}\) We fix the sign of subjective similarity with each source \((a_{ij} \text{ and } b_{ij})\) as our manipulation \((a^M_j \text{ and } b^M_j)\). Otherwise, we cannot identify the subjective correlations. The details of identification are outlined in Appendix.
specified as a function of balance status. Unlike $a_{ij}$ and $b_{ij}$, we allow $c_{ij}$ to have a different sign from the manipulated $c_j^M$. In this specification, the informational benefit depends on the sign of $a_{ij}b_{ij}c_{ij}$ which may differ from the sign of the manipulated variables $a_j^M b_j^M c_j^M$, so the informational benefit is not necessarily greater under imbalance $\left(a_j^M b_j^M c_j^M < 0\right)$ than balance $\left(a_j^M b_j^M c_j^M > 0\right)$. This allows us to test whether the informational benefit from search is different between balanced and imbalanced networks ($H2a$). Note that $\left(\theta_{bw}^{i0}, \theta_{bw}^{i1}\right)$ denotes parameters related to the subjective similarity between the two sources. For instance, if both $\theta_{bw}^{i0}$ and $\theta_{bw}^{i1}$ are positive, the valence of the product $a_{ij}b_{ij}c_{ij}$ is the same as that of $a_j^M b_j^M c_j^M$. This implies that, people find information under imbalanced networks more diagnostic than balanced networks as the normative model suggests. In contrast, if both $\theta_{bw}^{i0}$ and $\theta_{bw}^{i1}$ are negative, people find information under balanced networks more diagnostic than imbalanced networks. The diagnosticity of information under other possible combinations of $\theta_{bw}^{i0}$ and $\theta_{bw}^{i1}$ depend on the magnitude of the parameters. For instance, people find information under imbalanced networks more diagnostic than balanced networks when $\theta_{bw}^{i0}$ is not different from 0 but $\theta_{bw}^{i1}$ is positive (i.e., $a_{ij}b_{ij}c_{ij}$ is not different from 0 under balance, and $a_{ij}b_{ij}c_{ij} < 0$ under imbalance).

Finally, we allow for subjectivity in the prior and signal distributions as well. We cannot identify both subjective prior (i.e., aggregate) mean and variance jointly. See the Appendix for a discussion of model identification.

In Table 4b, we summarize the specification of attributes related to the perceived cost of search. For consumer $i$, let $\Delta_i$ denote a vector of all related individual-level parameters. The
parameter $\delta_{i0}$ captures consumer $i$'s (baseline) perceived cost of search. If the consumer has greater discomfort from gathering information from dissimilar others ($H1b$), the parameter $\delta_{i2}$ will be significantly positive. If a consumer experience greater discomfort from collecting and processing the information under an imbalanced social network ($H2b$), the parameter $\delta_{i3}$ will be significantly positive. Finally, we control for respondents’ fatigue.

7. Findings from Combining the Utility Model and Experimental Data

The model parameters are estimated using standard hierarchical Bayesian Markov chain Monte Carlo (MCMC) methods. We ran sampling chains for 200,000 iterations, and convergence was assessed by monitoring the time series of the draws. We report the results based on 100,000 draws retained after discarding the initial 100,000 draws as burn-in iterations. For each participant, we randomly select 15 of the 18 song profiles for model estimation and use the remaining 3 for out-of-sample prediction.

7.1 Model Comparison.

Table 5 reports the model fit of OL and SL models. We compared the two models on several measures of model fit. First, we report deviance information criterion (DIC) to evaluate within-sample fit and complexity of each model. Smaller numbers denote a better model (Spiegelhalter et al. 2002). Second, we computed within and out-of-sample hit rates. To assess the prediction for the purchase decision, we used purchase hit-rate with the cut-off fixed at 0.5. To evaluate the model prediction for search decision, we used search hit-rate. For computing the search hit rate, we discretized the observed $n_{ij}^{A*}$ and $n_{ij}^{B*}$ into 3 levels each based on their quartiles and thus the overall search decision, which is a combination of $n_{ij}^{A*}$ and $n_{ij}^{B*}$, is classified into 9 options. We also used 5 levels and 25 options. The search hit rate is the proportion of observations where the
observed search option matches the option with the highest search utility based on our model estimates. Third, we computed validation log-likelihood (VLL) in the holdout sample to assess predictive validity (Montoya et al. 2010; Iyengar and Jedidi 2012). The SL (Quasi-Bayesian) model outperforms the OL (Standard Bayesian) model on 3 of the 4 criteria.

Table 5 Model Comparisons

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>Search Hit Rate</th>
<th>Purchase Hit Rate</th>
<th>VLL</th>
<th>Search Hit Rate</th>
<th>Purchase Hit Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>9 groups</td>
<td>25 groups</td>
<td></td>
<td>9 groups</td>
<td>25 groups</td>
</tr>
<tr>
<td>OL</td>
<td>12,828.5</td>
<td>32.4%</td>
<td>20.1%</td>
<td>77.5%</td>
<td>-1,234.1</td>
<td>30.2%</td>
</tr>
<tr>
<td>SL</td>
<td>10,819.2</td>
<td>46.9%</td>
<td>29.9%</td>
<td>75.3%</td>
<td>-1,172.9</td>
<td>39.7%</td>
</tr>
</tbody>
</table>

7.2 Estimation Results.

Table 6 shows the estimation results from the two models. As is common in Bayesian analysis, we summarize the posterior distribution of the parameters by reporting their posterior means and 95% posterior confidence intervals. We present OL model results as a baseline, and use SL model results for hypotheses testing.

7.2.1 Hypotheses Tests.

Drivers of homophily. A significantly negative estimate of $\theta_1^{\text{with}}$ in Table 4 indicates that people perceive information from dissimilar others to be less diagnostic than that from similar others ($H1a$). In contrast, the insignificant estimate of $\delta_2$ shows that similarity does not have an effect on the level of discomfort ($H1b$). Our finding may appear inconsistent with past studies (e.g., Price and Feick 1984), but it is worth noting that there was no face-to-face social interaction in our setting. Thus, our results suggest that the discomfort people feel from getting information from others with dissimilar preferences need not be from processing the information (which was
part of our experiment), but may stem from having to interact with them (which was not part of our experiment).

**Table 6. Model Estimates for OL and SL models**

<table>
<thead>
<tr>
<th>Population Parameter Estimates</th>
<th>(a) OL (Baseline Model)</th>
<th>(b) SL (Proposed Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility parameters: Intercept ($\alpha_0$)</td>
<td>-0.10 (-0.24, 0.04)</td>
<td>0.25** (0.12, 0.38)</td>
</tr>
<tr>
<td>Utility parameters: Rating ($\text{Ln}(\beta)$)</td>
<td><strong>1.01</strong> (0.81, 1.22)</td>
<td>0.21* (0.03, 0.35)</td>
</tr>
<tr>
<td>Similarity with sources: Base ($\theta_0^{\text{with}}$)</td>
<td>(-0.20, -0.09)</td>
<td><strong>-0.14</strong></td>
</tr>
<tr>
<td>Similarity with sources: Dissimilar ($\theta_1^{\text{with}}$)</td>
<td>(-0.75, -0.36)</td>
<td><strong>-0.50</strong></td>
</tr>
<tr>
<td>Similarity between sources: Base ($\theta_0^{\text{bw}}$)</td>
<td>-0.10</td>
<td></td>
</tr>
<tr>
<td>Similarity between sources: Imbalance ($\theta_1^{\text{bw}}$)</td>
<td><strong>0.70</strong> (0.45, 0.92)</td>
<td>1.15** (1.01, 1.31)</td>
</tr>
<tr>
<td>Prior standard deviation: Base ($\theta_0^{\text{pri}}$)</td>
<td>(-0.27, 0.09)</td>
<td><strong>-0.40</strong></td>
</tr>
<tr>
<td>Signal standard deviation: Base ($\theta_0^{\text{sig}}$)</td>
<td>(-0.67, 0.11)</td>
<td></td>
</tr>
<tr>
<td>Perceived cost: Base ($\delta_0$)</td>
<td><strong>-0.80</strong> (-1.19, -0.41)</td>
<td>-0.36 (-0.77, 0.02)</td>
</tr>
<tr>
<td>Perceived cost: Order of songs ($\delta_1$)</td>
<td><strong>0.61</strong> (0.46, 0.76)</td>
<td><strong>0.65</strong> (0.50, 0.80)</td>
</tr>
<tr>
<td>Perceived cost: Negative ($\delta_2$)</td>
<td>(0.76)</td>
<td>-0.07 (-0.38, 0.15)</td>
</tr>
<tr>
<td>Perceived cost: Imbalance ($\delta_3$)</td>
<td><strong>-0.40</strong> (0.27, 0.54)</td>
<td></td>
</tr>
<tr>
<td>Scale parameter ($\text{Ln}(\lambda \times 10^3)$)</td>
<td><strong>1.83</strong> (1.57, 2.12)</td>
<td>0.42 (-0.03, 0.86)</td>
</tr>
</tbody>
</table>

Note: * denotes significance in 95% confidence level, and the corresponding intervals are in parentheses. ** denotes significance in 99%.

**Impact of Balance**: There are three notable findings for how balance impacts consumers’ decisions.

First, people ignore the similarity between information sources under balance and consider the sources to be uncorrelated (insignificant $\theta_0^{\text{bw}}$). Thus, people find the information under balance to be more diagnostic than what the normative model (OL) will imply. This finding is
consistent with the illusion of validity, which suggests that people falsely believe information from two highly redundant sources to be more diagnostic than what is implied by the statistics of correlation (Tversky and Kahneman 1974).

Second, in contrast, people do not ignore the similarity between information sources under imbalance. Note that the parameter $\theta_{bw}^1$ is positive, but smaller than 1. A positive $\theta_{bw}^1$ implies that the overall bias is reduced when people integrate the information from an imbalanced system. However, $\theta_{bw}^1 < 1$ implies that the magnitude of bias reduction under imbalance is not as large as what is predicted by OL model. In sum, people reduce their uncertainty more when the information is collected in imbalanced than balanced social systems ($H2a$) even if bias reduction under imbalance is not as large as normative prediction.

Third, as the positive estimate of $\delta_3$ shows, people have significantly greater discomfort of gathering and processing information in an imbalanced network than a balanced network ($H2b$). This result is consistent with Heider (1946) and we find that such cognitive discomfort is present even when collecting information from others with imbalanced preferences. In sum, our finding suggests that imbalanced relationships have a higher level of cognitive discomfort even when there is no real interaction with others, which is the case in our experimental setting.

In Web Appendix, we show that our key findings are robust to two different levels of wait time. This implies that our findings are not driven by the specific level of imposed wait time.

**7.2.2 Comparative Statics.**

As our model is nonlinear in parameters and they are estimated based on data from search and purchase decisions jointly, we use comparative statics to quantify the impact of antecedents on the search and purchase decisions separately. We do so for both OL and SL models to further showcase the differences between them.
Figure 5. Comparative Statics of Search and Purchase Decisions: Similar vs. Dissimilar

(a) OL: Search Amount

(b) OL: Purchase Likelihood

(c) SL: Search Amount

(d) SL: Purchase Likelihood

Note: For generating the figures, we only varied the relevance of one source \( \alpha^M \) and fixed all other attributes \( (R_j^M = 5, \tau_j^M = 2.5, \sigma_j^M = 1.25, b_j^M = 0.2, c_j^M = 0.0, \text{ and } order_j = 10) \). The figures show the average search amount and average purchase likelihood averaged across all respondents.

Figure 5 depicts the impact of the valence of similarity on consumers’ decisions. For these plots, we compute the search amount and purchase likelihood for each respondent from both models. Given the attribute values and the estimates of individual parameters, the plots show the average across all respondents. In the OL specification, where the diagnosticity of information
from similar or dissimilar others is forced to be identical, the valence of similarity cannot have an impact on either search or purchase decision (Figure 5a and 5b). In the SL specification, where we find that consumers deem information to be more diagnostic from similar others than dissimilar others, it is not surprising that people tend to search more from similar others (Figure 5c). Search amount is up to 50% greater when both sources have preferences similar to the information seeker than when only one of them has similar preference. Also, people purchase more when the information is collected from similar others (Figure 5d). Purchase likelihood is up to 8% greater when both sources have similar preference than when one of them has dissimilar preference.

Figure 6 depicts the impact of the balance on consumers’ decisions. As before, given the attribute values and the estimates of individual parameters, we compute the purchase likelihood and total search amount for each respondent from both models. The plots show the averages across all respondents. In the OL specification, where the diagnosticity of information is forced to be greater in an imbalanced network, the search amount and the purchase likelihood is always greater in an imbalanced network (Figure 6a and 6b). In the proposed SL model, however, people search less under imbalance because of greater cognitive discomfort (Figure 6c). People search up to 45% less under an imbalanced network than a balanced network. However, as the absolute similarity between sources increases, so does the informational benefit under imbalance thus shrinking the difference in the search amount between the two conditions. Notably, the lower amount of search under an imbalanced triad still leads to greater purchase likelihood (Figure 6d) as compared to the balanced condition because people can reduce their uncertainty to a greater extent under the former. Purchase likelihood is around 4% greater under an imbalanced triad than a balanced triad.
Figure 6. Comparative Statics of Search and Purchase Decisions: Balance vs. Imbalance

(a) OL: Search Amount

(b) OL: Purchase Likelihood

(c) SL: Search Amount

(d) SL: Purchase Likelihood

Note: For generating the figure, we only varied the relevance of one source \( c^M_j \) and fixed all other attributes \( R^M_j = 5, \tau^M_j = 5, \sigma^M_j = 2.5, a^M_j = 0.6, b^M_j = 0.3, \text{ and } order_j = 10 \). The figures show the search amount and purchase likelihood averaged across all respondents.

8. Conclusions

We conducted a detailed study about the impact of preference-induced homophily and balance on how consumers collect product information from social contacts and purchase products. In
contrast to typical past work using field data, we use an incentive compatible randomized experiment where consumers make purchase decisions for individual music tracks while having access to others’ evaluations.

8.1 Findings
Our results provide insights into the drivers that impact when consumers seek assistance from peers. First, as a complement to many studies that have focused on homophily based on socio-demographics, we present evidence of preference-based homophily. Using a utility-based model with quasi-Bayesian consumer learning, we disentangle whether this effect is due to either the greater diagnosticity of information from similar others or a reduction in the cognitive discomfort of seeking information from similar others. The results suggest that, in our context, the main driver is the former - consumers find reviews from similar others to be more diagnostic than those from dissimilar others. Second, the impact of balance on consumer learning from social contacts is nuanced: people prefer imbalanced systems for their higher diagnosticity of information, but balanced systems for their lower cost most likely due to the cognitive and affective burden of dissonance. Thus, people appear to understand that informational benefit is greater under an imbalanced social system but that it can be burdensome to gather and process the information. As we manipulated the similarity of preference among consumers, our results do not suffer from confounds such as interpersonal affect, higher frequency of interactions with similar others typically present in observational data.

8.2 Implications for Theory and Research
Our study will be interest to researchers who study different moderators of social learning and social contagion. For instance, Godes and Mayzlin (2009) show that, for products with low awareness (e.g., a brewery chain), word-of-mouth from less loyal customers is more effective
than more loyal customers at driving sales. Iyengar et al. (2011) consider the adoption of a new drug and find that physicians’ self-perceived opinion leadership moderates the weight they put on other physicians’ prescription behavior. There is evidence for social learning in online contexts as well. For example, in a study that investigated the spatial adoption of a new online retailer, Lee and Bell (2013) show how much neighbors trust and communicate with each other makes the social learning process more efficient. We add to this stream of literature by specifically considering how similarity of preference among information seekers and providers can moderate the level of social learning. In addition, most past work does not separate out passive exposure to information versus active search. This study focuses on the latter and shows that the amount of active search has a substantial impact on later purchase behavior.

Our results show that people understand that informational benefit is greater in an imbalanced social network but that it can be burdensome to process the gathered information. This underlying tension suggests the need for better understanding the drivers for optimal level of heterophily in social ties (e.g., Alpert and Anderson 1973). On the one hand, connections with others with dissimilar preferences can be conduits for novel information. Granovetter (1973) found that weak ties (e.g., acquaintances with perhaps less similar preferences) provide new information more so than strong ties. Similarly, Burt (1980) noted that individuals that span the structural holes in a network (i.e., have ties across different subgroups with potentially differing preferences) have an advantage in that they can broker the flow of information. On the other hand, gathering such information will come with a higher level of discomfort. How consumers strategically form ties with others to tradeoff information novelty and cognitive cost is a fruitful area of research.
On a related note, our results on the level of purchase show that there is a trade off from the two network antecedents of homophily and balance. On the one hand, search from similar others is more likely to converge to purchase than the same amount of search from dissimilar others. On the other hand, search in an imbalanced network is more likely to converge to purchase than the same amount of search in a balanced network. As typical social networks contain homophilous ties and are balanced, the two network antecedents have countervailing effects. Empirical research on trade-offs among network characteristics is scant with a notable exception being Aral and Van Alstyne (2011) on the diversity-bandwidth trade-off for the total amount of novel information. More work on how characteristics of social networks create opposing forces and drive customer behavior will be a fruitful area of future research.

Our study is in a context in which consumers gather product evaluations from their peers. Prior work, however, suggests that people are often persuaded more by experts than non-experts (e.g., Petty et al. 1981). We can speculate how our results may change when there is an expert source. It is possible that people may gather a large number of (if not all) evaluations from the expert. Recent research suggests otherwise. For instance, in pharmaceutical contexts where expertise should clearly matter and key opinion leaders play a critical role, modern medical literature has actually shown that local opinion leaders are more important than national leaders (e.g., Flodgren et al. 2011, Keating et al. 2007, Kuo et al. 1998). This is because nationally reputed “expert opinion leaders” are much less representative than local “peer opinion leaders” who are members of their own community and face similar patients and working conditions (Locock et al. 2001). Thus, even when expertise matters, similarity of preferences may continue to play an important role.
We focus on preference-based homophily. Much other work has considered demographics-based homophily (e.g., Centola and Van de Rijt 2014). Yaniv et al. (2011) speculate that these two types of similarities differ greatly in their strength and impact with behavioral similarity with an advisor stirring “hot” reactions while demographic similarity eliciting “cold” calculations. Clearly, more research on how different types of homophily may be activated in various contexts and their impact of behavior is warranted.

Finally, we contribute methodologically as well by proposing a Quasi-Bayesian consumer learning model, which is suitable when consumers learn from peers. We extend the standard multivariate Bayesian learning model, which allows for a correlation of information among different sources (Winkler 1981) in two ways. First, a consumer may purposely gather information from others who may have systematically different tastes compared to his own. This is unlike learning from own experience (e.g., Erdem and Keane 1996) or from targeted marketing activities such as detailing (e.g., Narayanan and Manchanda 2009) where the information provides unbiased signals for consumers’ evaluation. This is also unlike prior models of social learning (Roberts and Urban 1988; Erdem et al. 2005; Zhao et al. 2013) that assume social reviews provide unbiased signals. Second, social learning is allowed to be affected by behavioral aspects related to the similarity of preferences among information receivers and providers. For instance, people may perceive information from similar others to be more diagnostic than from dissimilar others. It will be useful to show the applicability of the proposed model in other contexts with learning from peers.

8.2 Implications for Marketing Practice

In the last few years, companies are actively embracing the notion of providing their customers with access to their friends’ evaluations. For instance, companies that facilitate social search (e.g.,
Facebook graph search, Bing social search) allow information seekers to search for content from their social contacts. With advertising being the major source of revenue for these websites, our results suggest that they may be able to increase their search traffic by making consumers perceive that the search results are from others whose preferences are similar to theirs and to each other. This strategy will increase the search clicks as people perceive that the results are informative (as they come from similar others), and less effortful to process (since they come from people in balanced networks).

Our findings are also relevant for companies that provide consumers with reviews for experiential products (e.g., Open Table for restaurants). Many of these websites wish to increase the purchase rate of products and are trying to do so by providing consumers with their friends’ reviews. For instance, Open Table receives commission from restaurants when a consumer reserves through the website. Our results suggest that Open Table (and other such websites) may be able to increase their purchase rate by making consumers perceive that the search results are from those who have similar preferences, but that they are also being exposed to others with diverse preferences. In sum, the top-line message to practitioners is that effective use of social recommendation systems involves paying careful attention to which social contacts consumers should access.
References


Web Appendix

1. Informational Benefit under OL Model

As a result of information update, we obtain the posterior belief about all three evaluations, 

\[ f^R (R | I(t_2)) \], which follows a multivariate normal distribution (for notation simplicity, we omit the subscripts for respondent and product). Thus, we can obtain a consumer’s posterior beliefs about their own song evaluation, 

\[ f^{RE} (R^E | I(t_2)) \], as a marginal distribution of 

\[ f^R (R | I(t_2)) \]:

\[ f^{RE} (R^E | I(t_2)) = N (PM, PV), \]  

(A1)

where \( PM = \omega^0 R^0 + \omega^A s^A + \omega^B s^B \),

\[ \omega^A = \frac{\tau^2 n^A n^A \left( a \left( N^B (\sigma^B)^2 + \tau^2 n^B \right) - b c \tau^2 n^B \right)}{N^A (\sigma^A)^2 + \tau^2 n^A} \left( N^B (\sigma^B)^2 + \tau^2 n^B \right) - c^2 \tau^4 n^A n^B, \]

\[ \omega^B_{ij} = \frac{\tau^2 n^B n^B \left( b \left( N^A (\sigma^A)^2 + \tau^2 n^A \right) - a c \tau^2 n^A \right)}{N^A (\sigma^A)^2 + \tau^2 n^A} \left( N^B (\sigma^B)^2 + \tau^2 n^B \right) - c^2 \tau^4 n^A n^B, \]

\[ \omega^0_{ij} = 1 - \omega^A_{ij} - \omega^B_{ij}, \]

and \( PV = \frac{\tau^2}{N^A (\sigma^A)^2 + \tau^2 n^A} \left( N^B (\sigma^B)^2 + \tau^2 n^B \right) - c^2 \tau^4 n^A n^B \)

\[ \times \left( \tau^2 n^A (1-a^2) + N^A (\sigma^A)^2 \left( \tau^2 n^B (1-b^2) + N^B (\sigma^B)^2 \right) - \tau^4 n^A n^B (ab-c)^2 \right). \]

The informational benefit refers to the amount of the uncertainty reduction after update. We operationalize the informational benefit (IB) as prior variance (i.e., how uncertain people are before the update) subtracted by the posterior variance (i.e., how uncertain people are after the update). For ease of exposition, we can rewrite IB as a function of absolute similarity with each
source (|a| and |b|) and absolute similarity between sources (|c|) in the following way.

\[
IB = \tau^2 - \frac{\tau^2 n^A \left(1 - |a|^2 \right) + N^A \sigma^A \left(1 - |b|^2 \right) + \tau^2 n^B \left(\tau^2 n^A + \tau^2 n^B \right) \left(2D|abc| - |ab|^2 - |c|^2 \right)}{\left(N^A \sigma^A + \tau^2 n^A \right) \left(N^B \sigma^B + \tau^2 n^B \right) - |c|^2 \tau^4 n^A n^B},
\]

(A2)

where \( D \) denotes an indicator of balance status which takes a value of 1 when \( abc>0 \) (balance), -1 when \( abc<0 \) (imbalance), and is 0 when \( abc=0 \).

**Sign of Similarity.** When the balance status \( (D) \) is held fixed, the sign of similarity per se does not affect the informational benefit. Suppose the similarity of a source \( (a) \) switches the sign, but balance status remains unchanged. We can think about a scenario where either \( D=0 \), or one of other similarity measures \( (b \) or \( c \)) also switches the sign when \( D \neq 0 \). Given that \( a \) enters Equation A2 only in absolute value, the sign of similarity per se will not affect informational benefit. The sign of similarity will change the informational benefit only through a change in the balance status of the system. Figure A1a depicts the property of OL that the sign of similarity does not have a direct impact on the informational benefit.

**Balance Status and Similarity between Sources.** Given all the other values fixed, we can immediately see that \( IB \) is always greater when \( D=-1 \) (imbalance) than when \( D=1 \) (balance). That is, the informational benefit is always greater under imbalance than balance.

Next, the result of comparative statics shows that the effect of similarity between sources \( (c) \) on the posterior variance is contingent on the balance status \( (D) \).

\[
\frac{\partial IB}{\partial |c|} = -\frac{2D\tau^6 n^A n^B \left(|a| N^B \sigma^B + (|a| - |bc|) \tau^2 n^A n^B \right) \left(|b| N^A \sigma^A + (|b| - |ac|) \tau^2 n^A n^B \right)}{\left(N^A \sigma^A + \tau^2 n^A \right) \left(N^B \sigma^B + \tau^2 n^B \right) - |c|^2 \tau^4 n^A n^B},
\]

(A3)
Given that the triadic similarity structure should be a proper covariance matrix, the sign of the first derivative is determined by balance status; it is positive when $D=-1$, and negative when $D=1$. In other words, the increase in the absolute similarity between sources ($|c|$) decreases (increases) the informational benefit under balanced (imbalanced) system. Figure A1b depicts the property of OL: The absolute similarity between sources cancels the noise of signals under imbalanced condition but amplifies it under a balanced condition, so informational benefit is always greater under imbalance.

**Figure A1. Informational Benefit under OL**

(a) Informational Benefit: Similar vs. Dissimilar

(b) Informational Benefit: Balance vs. Imbalance

Note: For generating Figure A1a, we varied the relevance of one source ($M_j^a$) and fixed all other attributes ($R_j^a = 0.5$, $\tau_j^a = 2.5$, $\sigma_j^a = 1.25$, $b_j^a = 0.2$, and $c_j^a = 0.0$). For generating figure A1b, we varied the relevance of one source ($M_j^c$) and fixed all other attributes ($R_j^c = 5$, $\tau_j^c = 2.5$, $\sigma_j^c = 1.25$, $a_j^c = 0.6$, and $b_j^c = 0.3$).

2. Model Estimation

We have 152 respondents ($i=1...N$), and each made search and purchase decisions for 18 songs ($j=1...J$). For respondent $i$ and song $j$, let $n_i^j$ denote the actual search decision and let $y_{ij}$ be an indicator variable that takes a value of 1 if he decides to purchase the song and is 0 otherwise.
We make the following distributional assumptions on the two errors in our model. First, the search utility error ($\xi_{n_{ij}}$) follows IID Type I Extreme value distribution with a scale parameter $\lambda_i$. Second, purchase utility error ($\epsilon_{ij}$) follows a standard Normal distribution. Then, the conditional likelihood that a consumer $i$ makes a search decision of $n_{ij}^*$ and purchase decision of $y_{ij}$ for a song $j$ can be expressed as:

$$
\Pr(n_{ij}^*, y_{ij} | \Gamma_i, \Delta_i, \Theta_i, \lambda_i) = \Pr(n_{ij}^* | \Gamma_i, \Delta_i, \Theta_i, \lambda_i) \times \Pr(y_{ij} | n_{ij}^*, \Gamma_i, \Theta_i),
$$

(A4)

where $\Gamma_i$ denote the vector of utility parameters $(\alpha_i, \ln(\beta_i))$ defined in the Equation 1. The first term on the right-hand side is the search likelihood which follows multinomial logit and the second term is the purchase likelihood which follows binary Probit.

In the experiment, search amount can be any combination of two integers between [0, 200]. As there are 40,401 possible options of search for each song, it is not feasible to estimate the model as is. We used a subset of options to estimate the model by the positive conditioning property (McFadden 1978; Train et al. 1987). For consumer $i$ and song $j$, let $W_{ij}$ denote a consideration set that includes the actual search option ($n_{ij}^*$) and 5 other possible options of $n_{ij}$, which are randomly selected from the empirical distribution of search decisions in our dataset.\(^1\)

Then, the search likelihood can be written as:

$$
\Pr(n_{ij}^* | \Gamma_i, \Delta_i, \Theta_i, \lambda_i) = \sum_{n_{ij} \in W_{ij}} \exp\left(\psi_i^h(n_{ij} | I_i(t_i), \Gamma_i, \Theta_i) / \lambda_i - \psi_i^e(n_{ij} | \Delta_i) / \lambda_i\right) \times h(W_{ij} | n_{ij}^*),
$$

(A5)

\(^1\) We also estimated a model where $W_{ij}$ consists of 10 alternatives including the observed search decision. All substantive findings remained unchanged. Research on case-control modeling indicates that little precision is gained by going beyond a 1-5 ratio of other alternatives (e.g., Donkers et al. 2003; Hu and Van den Bulte 2014).
where \( h(W_{ij} | n_{ij}) \) denotes a bias adjustment factor to account for using a subset of options.

Specifically, \( h(W_{ij} | n_{ij}) \) is the probability that consumer \( i \) formed a consideration set of \( W_{ij} \) given that he made a search decision of \( n_{ij} \). We used importance sampling and computed the bias adjustment factors from the empirical distribution of search decisions. Lastly, note that \( v_{ij}^b(\cdot) \) does not have a closed form expression (Equation 9) and is computed using a Monte-Carlo simulation.

The conditional purchase likelihood is a binary Probit likelihood specified as:

\[
Pr\left(y_{ij} | n_{ij}^*, \Gamma_i, \Theta_j \right) = \Phi\left(u_{ij}(I_i(t_2) | \Gamma_i, \Theta_j)\right)^{y_{ij}} \left(1 - \Phi\left(u_{ij}(I_i(t_2) | \Gamma_i, \Theta_j)\right)\right)^{1-y_{ij}},
\]

(A6)

where the information set in the second stage \((I_i(t_2))\) includes the search decision made in the first stage \((n_{ij}^*)\).

Given that there are common parameters \((\Gamma_i, \Theta_j)\) in both stages, the two decisions are estimated jointly. Therefore, the conditional likelihood of observing the decisions for consumer \( i \) for all \( J \) songs is:

\[
L_i | (\Gamma_i, \Delta_i, \Theta_i, \lambda_i) = \prod_{j=1}^{J} \Phi\left(u_{ij}(I_i(t_2) | \Gamma_i, \Theta_j)\right)^{y_{ij}} \left(1 - \Phi\left(u_{ij}(I_i(t_2) | \Gamma_i, \Theta_j)\right)\right)^{1-y_{ij}} \prod_{j=1}^{J} \frac{\exp\left(v_{ij}^b(n_{ij} | \Gamma_i, \Theta_j) / \lambda_i - v_{ij}^e(n_{ij} | \Delta_i) / \hat{\lambda}_i\right) \times h(W_{ij} | n_{ij})}{\sum_{n_{ij} \in W_{ij}} \exp\left(v_{ij}^b(n_{ij} | I_i(t_1), \Gamma_i, \Theta_j) / \lambda_i - v_{ij}^e(n_{ij} | \Delta_i) / \hat{\lambda}_i\right) \times h(W_{ij} | n_{ij})}.
\]

(A7)

To capture consumer heterogeneity, individual-level parameters \((\Gamma_i, \Delta_i, \Theta_i, \ln(\lambda_i))\) are assumed to be distributed multivariate normal with mean vector \((\Gamma, \Delta, \Theta, \ln(\lambda))\) and covariance matrix \( \Sigma \). The unconditional likelihood \( L \) for a sample of \( N \) customers is:
\[
L = \prod_{i=1}^{N} \int_{L_1} L_i |(\Gamma_i, \Delta_i, \Theta_i, \lambda_i) \ dF(\Gamma_i, \Delta_i, \Theta_i, \lambda_i | \Gamma, \Delta, \Theta, \lambda, \Sigma).
\]

where \( F(\Gamma_i, \Delta_i, \Theta_i, \lambda_i | \Gamma, \Delta, \Theta, \lambda, \Sigma) \) denotes the multivariate normal density function.

The model parameters are estimated using standard hierarchical Bayesian Markov chain Monte Carlo (MCMC) methods. We use the following set of priors for all population level parameters. Let \((\Gamma, \Delta, \Theta, \ln(\lambda))\) be a \(p \times 1\) vector and that \(\Sigma^{-1}\) is a \(p \times p\) matrix. Then, the prior for \((\Gamma, \Delta, \Theta, \ln(\lambda))\) is a multivariate normal with mean of 0 and covariance of \(0.1 \times I_{p \times p}\) matrix. The prior for \(\Sigma\) is a Wishart distribution where the scale matrix is \(0.1 \times I_{p \times p}\) matrix, and \(p+4\) degrees of freedom. The details of the full conditional distributions are available from the authors upon request.

3. Identification of Population Parameters

As summarized in Figure 2, informational benefit and perceived cost of search have asymmetric effects on search and purchase decisions: Both informational benefit and perceived cost drive search decision, but only informational benefit drives purchase decision given the search decision. Therefore, we can identify the parameters related to informational benefit with purchase observations given the search decisions, and identify the parameters related to perceived cost of search with search observations. Additionally, informational benefit derived from Bayesian learning mechanism further help us disentangle linear perceived cost from informational benefit.

In this section, we outline the identification of population parameters. Given the identification of population parameters \((\Gamma, \Delta, \Theta, \lambda)\), one can easily identify individual-level
parameters \((\Gamma, \Delta, \Theta, \lambda)\) with distributional assumptions on individual parameters (i.e., normally distributed around population parameters).

First, we can identify \(\Gamma\) and \(\Theta\) from observed purchase decisions given the search decisions. Observed purchase decisions with \(n_{ij}^* = (0, 0)\) can identify utility parameters \((\Gamma = [\alpha, \beta])\) and perceived prior variance \((\theta_{0}^{pri})\). Given that there was no search at all, the general tendency of purchase is captured by \(\alpha\), the effect of manipulated prior mean \((R_{j0}^{0M})\) on purchase is captured by \(\beta\), and the effect of manipulated prior standard deviation \((\tau_{j}^M)\) on purchase is captured by \(\beta\) and \(\theta_{0}^{pri}\). Thus, subjectivity in both prior mean and variance cannot be identified simultaneously.

The parameters related to perceived similarity with each source \((\theta_{0}^{with}, \theta_{1}^{with})\) are identified from observed purchase decisions given (1) no search from one source and (2) a sufficiently large amount of search from the other source (i.e., steady state where an additional signal hardly increase the search utility). For these observations, purchase utility depends only on parameters identified above (i.e., utility parameters and perceived prior variance) and perceived similarity with the source where the steady state is achieved \((a_j \text{ or } b_j)\). Therefore, general tendency of purchase among these observations identifies parameter \(\theta_{0}^{with}\), and the difference in purchase driven by the sign of similarity identifies \(\theta_{1}^{with}\).

The parameters related to perceived similarity between the two sources \((\theta_{0}^{bw}, \theta_{1}^{bw})\) are identified from the observed purchase decisions given a sufficiently large amount of search from
both sources. For these observations, purchase utility depends only on parameters identified so far (i.e., utility parameters, perceived prior variance, and perceived similarity with each source) and perceived similarity between the sources \( c_j \). Therefore, general tendency of purchase among these observations identifies parameter \( \theta_0^{red} \), and the difference in purchase driven by balance status identifies the parameter \( \theta_1^{red} \).

A general pattern of increase in purchase likelihood with respect to the amount of observed search \( n_j^* \) will identify the parameters of the perceived signal variance \( \theta_0^{sig} \).

Finally, we can identify discomfort-related parameters \( (\Delta) \) and scale parameter \( (\lambda) \) with observed search decisions. Given the identification of \( \Gamma \) and \( \Theta \), the expected informational benefit, \( v_j^\lambda(\cdot) \) in Equation 17, is identified. The effect of the expected informational benefit on search decision will identify \( \lambda \). The effect of \( (n_j^A,n_j^B) \) on the search decision captured through \( v_j^\epsilon(\cdot) \) will identify \( \delta_0 \). The parameter \( \delta_1 \) is identified from a systematic difference in \( v_j^\epsilon(\cdot) \) when signals are collected from a source with a negative similarity as opposed to a source with a positive similarity. Similarly, the parameter \( \delta_1 \) is identified from any systematic difference in \( v_j^\epsilon(\cdot) \) when signals are collected under an imbalanced system as opposed to a balanced system.

4. Robustness Check with Different Wait Time

In our experiment, respondents have to wait for half a second to retrieve a signal. This is to ensure that respondents take the search task seriously. To show that our key findings are not

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2 In our data, around 265 observations reached steady state (i.e., more than 20 signals collected) for both sources. Among those observations, 126 observations were under balance (48/126 converged to purchase), and 139 were under imbalance (53/139 converged to purchase). Therefore, we have sufficient information to identify \( (\theta_0^{bw}, \theta_1^{bw}) \).
driven by the chosen level of wait time, we collect data from a different group of respondents for whom the wait time to retrieve a quality signal is shorter (0.1 second) or longer (1 second). All other aspects of the experimental setting remain unchanged.

In the new data with different wait time, we replicate the simple analyses in Section 4.2 with the new data. As shown in Tables A1 and A2, the substantive findings from Section 4.2 are robust.

Table A1. Drivers for Search Decision with Different Wait Time

<table>
<thead>
<tr>
<th></th>
<th>(a) Shorter wait</th>
<th>(b) Longer wait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.23 (0.14)**</td>
<td>2.71 (0.07)**</td>
</tr>
<tr>
<td>Number of Dissimilar Sources</td>
<td>-0.14 (0.02)**</td>
<td>-0.11 (0.02)**</td>
</tr>
<tr>
<td>Imbalance</td>
<td>0.06 (0.05)</td>
<td>-0.01 (0.03)</td>
</tr>
<tr>
<td>Mean of Aggregate Evaluation</td>
<td>0.03 (0.01)**</td>
<td>0.05 (0.01)**</td>
</tr>
<tr>
<td>SD of Aggregate Evaluation</td>
<td>0.00 (0.02)</td>
<td>0.06 (0.02)**</td>
</tr>
<tr>
<td>Log(Order of song)</td>
<td>-0.04 (0.03)</td>
<td>-0.25 (0.02)**</td>
</tr>
</tbody>
</table>

Note: * p ≤ 0.05, ** p ≤ 0.01. Standard errors in parentheses

Table A2. Drivers of Purchase Decision with Different Wait Time

<table>
<thead>
<tr>
<th></th>
<th>(a) Shorter wait</th>
<th>(b) Longer wait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-2.47 (0.36)**</td>
<td>-1.45 (0.23)**</td>
</tr>
<tr>
<td>Number of Dissimilar Sources</td>
<td>-0.26 (0.12)*</td>
<td>-0.24 (0.09)**</td>
</tr>
<tr>
<td>Imbalance</td>
<td>0.44 (0.16)**</td>
<td>0.11 (0.13)</td>
</tr>
<tr>
<td>Mean of Aggregate Evaluation</td>
<td>0.45 (0.03)**</td>
<td>0.45 (0.02)**</td>
</tr>
<tr>
<td>SD of Aggregate Evaluation</td>
<td>0.16 (0.04)*</td>
<td>0.15 (0.06)**</td>
</tr>
<tr>
<td>Log(Search Amount+1)</td>
<td>0.23 (0.08)**</td>
<td>0.34 (0.07)**</td>
</tr>
<tr>
<td>Social Information Content</td>
<td>0.09 (0.01)**</td>
<td>0.12 (0.01)**</td>
</tr>
<tr>
<td>Social Information Content × Number of Dissimilar Sources</td>
<td>-0.06 (0.01)**</td>
<td>-0.09 (0.01)**</td>
</tr>
<tr>
<td>Social Information Content × Imbalance</td>
<td>0.06 (0.02)**</td>
<td>0.14 (0.02)**</td>
</tr>
</tbody>
</table>

Note: * p ≤ 0.05, ** p ≤ 0.01. Standard errors in parentheses

We also replicate the key results from the structural model estimation outlined in Section 7.2. As shown in Table A3, substantive findings remain robust to the change in the wait time.
Table A3. Model Estimates for SL with Different Wait Time

<table>
<thead>
<tr>
<th>Population Parameter Estimates</th>
<th>(a) Shorter wait Estimate (95% C.I.)</th>
<th>(b) Longer wait Estimate (95% C.I.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility parameters: Intercept ($a_0$)</td>
<td>0.00 (-0.17, 0.12)</td>
<td>0.38** (0.24, 0.53)</td>
</tr>
<tr>
<td>Utility parameters: Rating ($\ln(\beta)$)</td>
<td>0.49** (0.26, 0.75)</td>
<td>0.52** (0.32, 0.73)</td>
</tr>
<tr>
<td>Similarity with sources: Base ($\theta^\text{with}_0$)</td>
<td>-0.57** (-0.78, -0.40)</td>
<td>-0.47** (-0.62, -0.33)</td>
</tr>
<tr>
<td>Similarity with sources: Dissimilar ($\theta^\text{with}_1$)</td>
<td>-0.21* (-0.39, -0.04)</td>
<td>-0.25** (-0.38, -0.08)</td>
</tr>
<tr>
<td>Similarity between sources: Base ($\theta^\text{bw}_0$)</td>
<td>-0.10, 0.35</td>
<td>-0.23</td>
</tr>
<tr>
<td>Similarity between sources: Imbalance ($\theta^\text{bw}_1$)</td>
<td>0.11 (0.33, 0.81)</td>
<td>0.74** (0.44, 0.91)</td>
</tr>
<tr>
<td>Prior standard deviation: Base ($\theta^\text{pri}_0$)</td>
<td>-0.64, -0.04</td>
<td>-0.73** (-0.93, -0.54)</td>
</tr>
<tr>
<td>Signal standard deviation: Base ($\theta^\text{sig}_0$)</td>
<td>-0.09, 0.79</td>
<td>-0.16, 0.48</td>
</tr>
<tr>
<td>Perceived cost: Base ($\delta_0$)</td>
<td>-1.28, -0.43</td>
<td>-0.22, 0.53</td>
</tr>
<tr>
<td>Perceived cost: Order of songs ($\delta_1$)</td>
<td>0.13 (0.00, 0.26)</td>
<td>0.45** (0.31, 0.59)</td>
</tr>
<tr>
<td>Perceived cost: Negative ($\delta_2$)</td>
<td>-0.19 (-0.45, 0.08)</td>
<td>0.05</td>
</tr>
<tr>
<td>Perceived cost: Imbalance ($\delta_3$)</td>
<td>0.49** (0.26, 0.75)</td>
<td>0.34** (0.17, 0.51)</td>
</tr>
<tr>
<td>Scale parameter ($\ln(\lambda \times 10^3)$)</td>
<td>0.60* (0.12, 1.04)</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Note: * denotes significance in 95% confidence level, and the corresponding intervals are in parentheses. ** denotes significance in 99%.

Additional References (Appendix)


