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**Multi-Dimensional Observational Learning in Social Networks:
Theory and Experimental Evidence**

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Multi-Dimensional Observational Learning in Social Networks: Theory and Experimental Evidence[1]

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Abstract

The prevalence of consumers sharing their purchases on social media platforms (e.g., Instagram, and Pinterest) and the use of this information by potential future consumers have substantial implications for online retailing. In this study, we examine how product characteristics and the type of information provider jointly moderate the purchase decision in a social network setting. We first propose an analytical observational learning framework integrating the impact of product differentiation and social ties. Then, we use two experimental studies to validate our analytical results and provide additional insights. Our key findings are that the effect of learning from strangers is stronger for vertically differentiated products than for horizontally differentiated products. However, the effect of learning from friends does not depend on whether the underlying product is horizontally or vertically differentiated. What is more interesting is the nuanced role of social ties: For horizontally differentiated products, the effect of learning increases with the strength of social ties. In addition, "contact-based" tie strength is more important than "structure-based" tie strength in accelerating observational learning. These findings provide a motivation for online retailers to generate alternative strategies for increasing product sales through social networks. For example, online retailers offering horizontally differentiated products have strong incentives to cooperate with social media platforms (e.g., Instagram and Pinterest) in encouraging customers to share their purchase information.

Keywords: Multi-Dimensional Observational Learning, Social Ties, Product Differentiation

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1. Introduction

1.1 Motivation and Research Focus

Consider the following:

> Instagram is the quintessential example of social media users sharing their information with others through pictures instead of words. According to an article in Retail Dive, in 2017, 72% of Instagram users made purchase decisions after seeing something on Instagram, with the most common categories being clothing, makeup, shoes, and jewelry.[5]
>
> In a similar vein, Pinterest, an image-based social platform, has product rich pins that facilitate users to discover new products: In 2016, 55% of U.S. online users shared that their primary use of Pinterest was to find and/or shop for products.[6]
>
> According to a joint study by Twitter and analytics firm Annalect, around 40 percent of respondents surveyed indicated that they have purchased an item online after seeing it used by an influencer on Instagram, Twitter, Vine or YouTube.[7]
>
> Amazon has also launched its own social networking feature for product discovery called Amazon Spark, which allows its members to share the products they purchased.[8]

Two common threads emerging from these observations are as follows. First, the unprecedented growth of social network users in the last decade has resulted in significant increases in the availability of individual specific information such as holiday pictures, mobile check-ins at restaurants, to everyday purchases (Susarla et al. 2012, Bai et al. 2017, Huang et al. 2017, Sun et al. 2017, Qiu et al. 2018). Second, consumers shopping through social network channels are increasingly using this information in making their purchase decisions (Newberry

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[5] See https://www.retaildive.com/news/study-instagram-influences-almost-75-of-user-purchase-decisions/503336/ (last accessed: May 27, 2018).
[6] See http://www.businessinsider.com/pinterest-is-the-top-social-network-among-online-shoppers-2016-6 (last accessed: May 27, 2018).
[7] See https://www.adweek.com/digital/twitter-says-users-now-trust-influencers-nearly-much-their-friends-171367 (last accessed: May 27, 2018).
[8] See https://techcrunch.com/2017/07/18/amazon-launches-spark-a-shoppable-feed-of-stories-and-photos-aimed-at-prime-members/ (last accessed: May 27, 2018).

2016, Qiu and Whinston 2017, Li and Wu 2018, Xu and Liu 2018). These aspects motivate the overall focus of this paper: *In a social network setting, how do consumers evaluate available prior information to make a product purchase decision*?

In addressing this overall question, we draw upon observational learning as a mechanism by which customers evaluate prior information in making their decision. The classical example of observational learning is to choose a restaurant to dine in by observing the number of people already dining in that restaurant (Bannerjee 1992). In a social network setting, we adapt and extend the observational learning framework for: (a) different product types; and (b) prior purchase information provided by two groups.

The observed diversity of product offerings on a social network leads us to integrate products with different attributes. One approach to classify product types by distinct attributes is to consider how these attributes drive consumer choice, i.e., a classification of products with vertically and/or horizontally differentiated attributes. A vertically differentiated attribute is one where all consumers agree on whether they would prefer more or less of it (e.g., all consumers prefer a product with higher quality). Alternatively, a horizontal attribute is one where consumer preferences are dependent on a "taste" match (e.g., depending upon their "taste," some customers will prefer an Asian restaurant while others might prefer an Italian restaurant) (Chen and Xie 2005).

Since "ties" between "friends" and "strangers" are a common approach to identify individual relationships within social networks, we use this as a basis to categorizing available prior information for an individual consumer. Although information from family and "friends" has been shown to influence individual's purchase decisions in social networks (Zhang et al. 2015), nonetheless 84% of millennials state that user generated content from "strangers" has at least some influence on what they buy.[9]

1.2 Research Questions and Contributions

Prior studies in observational learning within social networks focuses on *one-dimensional* learning (e.g., consumers infer a products' vertically differentiated attribute such as quality through observing friends or strangers' behavior). To the best of our knowledge, there is little (if any) prior research on examining how product differentiation (vertical differentiation and/or horizontal differentiation) moderates the magnitude of observational learning. Products purchased on social networks could be both vertically <u>and</u> horizontally differentiated. For example, consider iPhones with distinct internal memory (e.g., 64GB or 256GB) and available in different colors (e.g., silver or black). Although all consumers might prefer greater internal memory (vertically differentiated attribute), the preferences for color (horizontally differentiated attribute) are consumer specific. Based on this, our methodological contribution is to develop an analytical framework for *multi-dimensional* observational learning: consumers can infer both vertical and horizontal product attributes through observing others' actions.

This framework is used to address our first research question: *What is the impact of product differentiation on the magnitude of observational learning? More specifically, we are interested in assessing whether observational learning is stronger for vertically differentiated products than for horizontally differentiated products?* On the one hand, consumers' purchase decisions may contain

[9] See https://www.gartner.com/smarterwithgartner/fuel-social-marketing-user-generated-content/ (last accessed: May 27, 2018).

more useful information for vertically differentiated products than for horizontally differentiated products. For the latter, purchasing a product may simply reflect another consumer's preference instead of the underlying vertical attribute associated with the former. On the other hand, one could also argue that the informational value of purchasing a horizontally differentiated product is larger than that of purchasing a vertically differentiated product. The reason is that observing others' purchase decisions of a horizontally differentiated product leads to multi-dimensional learning, which allows consumers to infer both vertical and horizontal attributes. Our finding is that the magnitude of observational learning for vertically differentiated products is moderated by the correlation between the individual consumer's perception of the horizontally differentiated attribute and the information availability from either a friend or a stranger. If this correlation is weak (the case of strangers), the effect of learning is stronger for vertically differentiated products than for horizontally differentiated products; while if the correlation is strong (the case of friends due to the homophily effect), effect of learning for vertically differentiated products is similar to that for horizontally differentiated products. These findings are confirmed by our experimental evidence.

Since prior research has not directly addressed the interaction between the strength of social ties and product differentiation in the context of observational learning, the proposed analytical framework is also useful to address our second research question: *What is the effect of social ties on the magnitude of observational learning for vertically versus horizontally differentiated products?* Our key finding is that for horizontally differentiated products, the effect of learning from friends is stronger than that from strangers; while for vertically differentiated products, the effect of learning from friends is similar to that from strangers.

The analytical findings are supplemented with results from hypotheses tested in experimental settings. We find strong support for all hypotheses in our first experiment. To further quantify social tie strength, a second experiment (using data from Facebook API) uses three measures of social ties between subjects: (a) Embeddedness (shared friends on Facebook); (b) Tagged photos; and (c) Shared wall posts. This experiment, with more field elements, controls for artificial social ties in typical laboratory settings. The key finding is that for horizontally differentiated products, learning effects using information provided by friends are increasing in the strength of social ties and this holds regardless of the measure used. To observe the effects of the measures on learning, the three social tie measures are grouped into "contact-based" measures (recording the number of interactions between an individual and a friend) and "structure-based" measures (capturing the idea of different groups) (Gee et al. 2017). Our findings are that contact-based measures are more effective than structure-based measures to accelerate observational learning.

The remainder of this paper is organized as follows. In the next section, we discuss the existing literature and in Section 3, we introduce the analytical framework and describe the results stemming from the analysis. In Sections 4 and 5, we discuss the results of two experimental studies for testing the hypotheses. Finally, implications and conclusions are presented in Section 6.

2. Literature Review

In this section, we review the relevant literature classified into: (i) Analytical models; (ii) Empirical studies, and (iii) Experimental studies. We also highlight our extensions/contributions as they relate to each of these areas.

2.1 Literature on Analytical Observational Learning Models

From an observational learning perspective, the seminal studies consider a setting where individuals sequentially make decisions by observing an independent private signal about product quality and learn useful information from observing the actions of all the previous decision-makers (Banerjee 1992, Bikhchandani et al. 1992). Two critical assumptions in this stream of research are that:

- *Assumption 1*: The product is vertically differentiated.
- *Assumption 2*: Individuals can observe the decisions of *all* previous decision makers in the sequential learning process.

Since our focus is on social networks where products available could be both vertically and horizontally differentiated (Chen and Xie 2005, Hong and Pavlou 2014, Kwark et al. 2014), our analytical approach completely relaxes Assumption 1. Although there is one approach examining learning effects for horizontally differentiated products (Hendricks et al. 2012), the proposed approach is comprehensive since it captures learning effects for products either vertically <u>or</u> horizontally differentiated.

A handful of prior studies investigate relaxing Assumption 2 from different perspectives. Guarino et al. (2011) model imperfect observability of other individuals' actions and assume that a consumer can only observe the aggregate purchase decision of the predecessors. Motivated by the social sharing feature on Facebook, a recent research stream focuses on observational learning in social networks and the role of network topology: People connected in social networks can only observe friends' choices (Acemoglu et al. 2011, Zhang et al. 2015, Qiu and Whinston 2017). Our observation is that on social networks, a user has access to prior information from both friends and strangers. Thus, the proposed approach integrates information availability from both these sources.

Another classification of product attributes could be search or experience goods. Search goods are defined as those dominated by product attributes for which full information can be acquired prior to purchase while experience goods have attributes that cannot be known until the actual purchase of the product (Nelson 1970). While there are papers on observational learning for experience goods (Shi and Whinston 2013) and search goods (Hendricks et al 2012), in this paper, we are focused on describing the effect of observational learning for products that have both horizontal and vertical attributes.

2.2 Empirical Observational Learning Studies

There are several empirical studies assessing learning effects (using archive data) in different contextual settings such as software adoption (Duan et al. 2009), kidney market (Zhang 2010), movie sales (Moretti 2011), online deals (Chen et al. 2011), online microloan markets (Zhang and Liu 2012), and the digital music market (Newberry 2016). Li and Wu (2017) differentiate between the effects of observational learning and word of mouth.

From a social network perspective, Shi and Whinston (2013) and Qiu et al. (2018) examine learning within location-based social networks. In the latter study, Qiu et al. (2018) estimate an empirical model of restaurant discovery and observational learning which allows them to separate observational learning from non-informational confounding mechanisms, such as homophily. Lee et al. (2015) examine the differential impact of prior movie ratings by strangers versus friends and find that friends' ratings always induce herding.

Our contributions to this empirical stream of work is that it provides an analytical framework as well as empirical evidence to investigate the interaction between product differentiation and social ties when using observational learning.

2.3 Experimental Studies on Observational Learning

The experimental literature either provides evidence for the existence of observational learning or attempts to separate observational learning from other confounding factors. For example, Cipriani and Guarino (2005) find a significant observational learning effect in a laboratory financial market while Georee et al. (2007) find that agents tend to pay more attention to their own signals and less to past publicly observed choices in the context of observational learning. In a field experiment, Cai et al. (2009) distinguish between observational learning from saliency effects. Our experimental work extends this prior research by exploring how product differentiation and social ties moderate the impact of observational learning. This allows us to examine how learning effects vary by product type as well as types of information.

Our work is also related to prior experimental evidence on the impact of social ties. Using field experiments, Bakshy et al. (2012) and Aral and Walker (2014) find that a strong tie is more influential than a weak tie in information propagation. Bapna et al. (2017a, b) investigate the effect of social ties on trust formation and forgiveness. Instead of such a focus, we examine how social ties and product differentiation together influence observational learning.

In the section that follows, we describe our stylized analytical framework. Following a discussion of key results, we conclude with a set of hypotheses.

3. A Simple Analytical Framework

3.1 Preliminaries

Consider a representative consumer i making the decision whether to purchase a product. The product has both vertical (quality) and horizontal (taste) dimensions. In the vertical dimension, all consumers agree on the preference order of an attribute; while on the horizontal dimension, consumers have heterogeneous tastes for the same attribute (Chen and Xie 2005).

In the vertical dimension, the quality of the product is unknown and is represented by a binary random variable: $V \in \{V_H, V_L\}$, and $V_L = \alpha V_H$, where $0 < \alpha < 1$. Following the classical observational learning literature (Bikhchandani et al. 1992), we assume a common prior on the probability that the product is of high or low quality: $\Pr(V_H) = \Pr(V_L) = 1/2$.[10]

In the horizontal dimension, consumer *i* has an exogenous taste for the product. Following Chen and Xie (2008), we assume the exogenous taste as a preference matching process. The type of the product is unknown and is represented by a binary random variable: $\Pi \in \{T_0, T_1\}$. Similarly, consumer i's type is $T_i \in \{T_0, T_1\}$, which is the consumer's private information. Assuming a common prior on the distribution of types: The types Π and T_i are independently drawn from a

[10] This assumption is consistent with the Bayesian tradition of uninformative priors (Berger 2006): The principle of maximum entropy is often used to obtain prior probability distributions for Bayesian inference, and in our discrete distribution, $\Pr(V_H) = \Pr(V_L) = 1/2$ maximizes the entropy (Jaynes 1968).

Bernoulli distribution with $\Pr(T_0) = \Pr(T_1) = 1/2$. If $\Pi = T_0$, $T_i = T_0$, or $\Pi = T_1$, $T_i = T_1$, we call that the taste is matched, otherwise the taste is not matched.

The payoff function of consumer i depends on her purchase decision, the price of the product, the quality of the product, and whether the taste is matched. If consumer i purchases the product, her payoff function is given as follows:

$$u_i = V - r \cdot I_{\{unmatched\}} - p, \tag{1}$$

where $I_{\{unmatched\}}$ is an indicator function, which takes the value of one if the taste is not matched, and takes the value of zero if the taste is matched, and p is the product price. If the product does not match the consumer's taste, there is an unmatched cost, r. We assume that the product price, p, is exogenously given, and we set it to be the consumer's ex-ante expected value gained from the product:

$$p = \mathbb{E}\left[V - r \cdot I_{\{unmatched\}}\right] = \frac{1}{2}V_H + \frac{1}{2}V_L - \frac{1}{2}r = \frac{1+\alpha}{2}V_H - \frac{1}{2}r. \tag{2}$$

Since our focus is <u>not</u> on dynamic pricing in the presence of observational learning (as in Jing 2011, Garcia and Shelegia 2018), a consumers' ex-ante expected value is also the optimal (ex-ante) price charged by the firm given that a consumer will purchase the product only when $\mathbb{E}[u_i|I_i] > 0$, where I_i is consumer i's information set. This is also consistent with the settings in prior literature on observational learning (Qiu and Whinston 2017). Table 1 provides a list of the notations used in the model and all proofs are relegated to Appendix A.

Table 1. Summary of Notations

Notation	Description
V_H, V_L	Product quality
S_H, S_L	Private signal on product quality
T_0, T_1	Product/consumer types
S_0, S_1	Private signal on product types
q	Precision of the private signal on product quality
w	Precision of the private signal on product types
p	Product price
r	Unmatched cost
α	$V_L = \alpha V_H$, and $0 < \alpha < 1$

3.2 Analytical Results

Consider a generic consumer *j* of type $T_j = T_0$. Prior to making a decision, she can access binary private signals about the product quality and product types. The signal on product quality can be either S_H or S_L, and satisfies: $\Pr(S_H|V_H) = \Pr(S_L|V_L) = q$, $\Pr(S_L|V_H) = \Pr(S_H|V_L) = 1 - q$, where $1/2 < q < 1$. The signal on product types can be either S_0 or S_1, and satisfies: $\Pr(S_0|T_0) = \Pr(S_1|T_1) = w$, $\Pr(S_1|T_0) = \Pr(S_0|T_1) = 1 - w$, where $1/2 < w < 1$. Note that q and w measure the precision of the signals. $q > 1/2$ implies that if the product quality is V_H (V_L), consumer *j* is more likely to receive S_H (S_L). Similarly, $w > 1/2$ implies that if the product type is T_0 (T_1), consumer *j* is more likely to receive S_0 (S_1). If q or w is higher, the signal is more informative.

The following lemma characterizes consumer *j*'s decision rule.

Lemma 1. *If consumer j of type $T_j = T_0$ receives signals S_H and S_0, she will always purchase the product; if consumer j receives signals S_L and S_1, she will NOT purchase the product; if consumer j receives signals S_H and S_1, she will purchase the product when $\frac{V_H(1-\alpha)}{r} > \frac{w-\frac{1}{2}}{q-\frac{1}{2}}$; if consumer j receives signals S_L and S_0, she will purchase the product when $\frac{V_H(1-\alpha)}{r} < \frac{w-\frac{1}{2}}{q-\frac{1}{2}}$.*

Although only stated for a consumer of type T_0, the underlying logic of Lemma 1 also applies for a consumer of type T_1. The results are that for a representative consumer j:

- Always purchase the product if her private signals favor high quality and matched taste;
- Do not purchase the product if her private signals favor low quality and unmatched taste; and
- If her private signals favor high quality but unmatched taste, she will purchase the product provided the ratio of quality mismatch to cost of "taste" mismatch is large (or the precision of the taste to quality signal is low); else she will not purchase the product;
- If her private signals favor low quality but matched taste, she will purchase the product provided the ratio of quality mismatch to cost of "taste" mismatch is small (or the precision of the taste to quality signal is high); else she will not purchase the product.

When $V_H(1-\alpha)$ is larger (smaller) relative to *r*, the quality differential is larger (smaller) relative to the taste cost and thus, the product is more (less) vertically than horizontally differentiated. Correspondingly, when $w-\frac{1}{2}$ is larger (smaller) relative to $q-\frac{1}{2}$, the precision of the signal corresponding to product type is greater (lesser) than the signal corresponding to quality and thus, there is better information available for the horizontal (vertical) attribute than the vertical (horizontal) attribute.

The intuition behind Lemma 1 is as follows. When both of the signals favor desirable outcomes (high quality in the vertical dimension and matched taste in the horizontal dimension), consumer j will purchase the product. When both of the signals favor undesirable outcomes (low quality in the vertical dimension and unmatched taste in the horizontal dimension), consumer j will not purchase the product. In the following two more complicated scenarios, consumer j receives one signal that favors a desirable outcome, and the other signal that favors an undesirable outcome: (i) Consumer *j* receives a quality signal that favors the desirable outcome in the vertical dimension and a taste signal that favors the undesirable outcome in the horizontal dimension. (ii) Consumer *j* receives a taste signal that favors the desirable outcome in the horizontal dimension and a quality signal that favors the undesirable outcome in the vertical dimension. In these two scenarios, consumer *j* should make her decision based on the relative weight of the quality and taste components in her payoff function. If the quality component is more important ($\frac{V_H(1-\alpha)}{r}$ is large), consumer *j* will follow the quality signal: She will purchase the product in scenario (i), and not purchase the product in scenario (ii). If the taste component is more important ($\frac{V_H(1-\alpha)}{r}$ is small), consumer *j* will follow the taste signal: She will not purchase the product in scenario (i), and purchase the product in scenario (ii).

3.3 Information Provider Dynamics

How do the characteristics of the information provider relate to the decision for a typical consumer? In order to address this issue, we consider two cases. In the first case, this typical consumer observes a stranger's decision, and in the second case, she observes her friend's decision.

3.3.1 Observing a Stranger's Decision

We assume that before consumer *i* makes her decision, she is able to observe a stranger, consumer *j*'s decision. Because consumer *i* and consumer *j* are strangers, we assume that consumer *i* does not know consumer *j*'s type, but she knows consumer *j*'s type is drawn from a Bernoulli distribution with $\Pr(T_0) = \Pr(T_1) = 1/2$. The realization of consumer *j*'s type is $T_j \in \{T_0, T_1\}$.

Without loss of generality, we assume that $T_j = T_0$. The same logic follows if $T_j = T_1$.

Consumer *j* has faced a similar decision problem and has made her decision. Consumer *j*'s payoff function is the same as consumer i's: $u_j = V - r \cdot I_{\{unmatched\}} - p$. The only difference between consumers *i* and *j*'s decision problem is that consumer *j* receives private signals about product quality, V, and product type, Π. These private signals that consumer *j* receives could be interpreted as private information that the consumer has regarding the quality of the product (Welsh 1992). However, consumer *i* does not have access to this private information. This is realistic in scenarios where consumer *j* is an early adopter and consumer *i* is a late adopter. Thus, consumer *i* makes her purchase decision after observing the decision made by consumer *j*. The essence of observational learning in our context is that consumer *i* cannot directly observe these signals that are known to consumer *j* privately, but she can infer consumer *j*'s private information from consumer *j*'s decision.

Consumer *i* observes consumer *j*'s decision (a stranger's decision), and makes her own decision. From consumer *j*'s decision (purchase or not), consumer *i* may learn useful information. In the following two propositions, we present the results of observational learning from a stranger's decision, which critically depend on whether the product is more quality oriented or taste oriented.

Proposition 1. *In the context of learning from a stranger, if the product is more quality oriented, i.e.,* $\frac{V_H}{r} > \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$, *consumer i will follow consumer j's decision (a stranger's decision): Consumer i will purchase the product when consumer j purchases the product; consumer i will not purchase the product when consumer j does not purchase the product.*

Proposition 2. *In the context of learning from a stranger, if the product is more taste oriented, i.e.,* $\frac{V_H}{r} < \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$*, consumer i will ignore consumer j's decision (a stranger's decision) and use her own information to make the decision.*

Proposition 1 shows that since the learning effect from a stranger is very strong when the product is more vertically differentiated, consumer *i* will completely follow consumer *j*'s decision. However, Proposition 2 demonstrates that this learning effect from a stranger does not exist when the product is more horizontally differentiated. In particular, in the case of Proposition 2, consumer *i* will be indifferent between purchasing and not purchasing the product since her prior information implies that $\mathbb{E}[u_i] = 0$.

Why does the effect of observational learning from a stranger depend on whether the product is quality or taste oriented? In our multi-dimensional learning model, consumer *i* may learn from consumer *j*'s decision in two potential dimensions: (i) the vertical dimension, i.e., whether consumer *j* receives a signal favoring high quality; and (ii) the horizontal dimension, i.e., whether consumer *j* receives a signal favoring matched taste. The key is that consumer *i* does not know consumer *j*'s type because they are strangers. In other words, there is no additional value for consumer *i* to have better information on whether consumer *j*'s type matches the product type because consumer *j*'s type is unknown to consumer *i*. Therefore, the learning process in the horizontal dimension is blocked. On the other hand, for a quality-oriented product, consumer *i* is able to infer the underlying quality very well through observational learning from a stranger's decision.

3.3.2 Observing a Friend's Decision

In this scenario, before consumer i makes her decision, she is able to observe a friend, consumer k's decision. In prior literature, homophily is a typical phenomenon observed in social networks in which there are inherent similarities in friends' personal characteristics (Aral and Walker 2011, Gu et al. 2014, Qiu et al. 2017). In other words, homophily refers to the tendency of individuals to associate with similar others, as in the proverb "birds of a feather flock together." Following the idea of homophily, we assume that consumers i and k have the same type (same taste) because they are friends. Other model settings are the same as the case of learning from a stranger. In the following proposition, we present the results of observational learning from a friend's decision.

Proposition 3. *In the context of learning from a friend, consumer i will follow consumer k's decision (a friend's decision) no matter if the product is more quality oriented or more taste oriented: Consumer i will purchase the product when consumer k purchases the product; consumer i will not purchase the product when consumer k does not purchase the product*.

Proposition 3 shows that unlike learning from a stranger, the effect of observational learning from a friend does not depend on whether the product is more quality oriented or more taste oriented. Consumer i will completely follow his friend's decision. The reason is that consumer i knows that she has the same type as consumer k, and consumer k has more information (private quality and taste signals). Given that consumer k has made a rational decision, consumer i should completely follow her friend's decision. Recall that in the case of learning from a stranger, the situation is different: Consumer i is not sure if she has the same type as the stranger, consumer j.

The results of Propositions 1, 2, and 3 are summarized in Table 2 below.

Table 2. The Effect of Observational Learning in Different Cases

	Learning from a stranger	Learning from a friend
Vertically differentiated product	Follow the stranger's decision	Follow the friend's decision
Horizontally differentiated product	Ignore the stranger's decision	Follow the friend's decision

3.4 Hypotheses

Our analytical results are that the effect of learning on the purchase decision is contingent on the type of product and the information provider. This leads us to formulate the following hypotheses.

Hypothesis 1 (H1). *The effect of learning from strangers is stronger for vertically differentiated products than for horizontally differentiated product:* (i) *For vertically differentiated products, a consumer tends to follow the previous stranger's decision;* (ii) *but for horizontally differentiated products, a consumer tends to ignore the previous stranger's decision.*

Hypothesis 2 (H2). *The effect of learning from friends does not depend on whether the underlying product is vertically or horizontally differentiated and a consumer tends to follow a friend's decision.*

Hypothesis 3 (H3). *(i) For horizontally differentiated products, the effect of learning from friends is stronger than that from strangers. (ii) For vertically differentiated products, the effect of learning from friends is similar to that from strangers.*

In the next two sections, we describe the results of two experimental studies for testing these hypotheses.

4. Experimental Study 1

4.1 Experimental Design

In our study 1, we conduct a controlled laboratory experiment to test hypotheses derived from our analytical framework. Controlled economic experiments are increasingly useful to strengthen internal validity and establish causal relations (Bapna et al. 2010, Rice 2012, Qiu et al. 2014, Yin et al. 2014, Gupta et al. 2017, Adomavicius et al. 2018). In our context, the laboratory setting allows us to control for many confounding factors. Although laboratory experiments may not promise quantitative external validity, they can provide qualitative external validity if the observed relationship is monotonic and does not change direction when changing the level of variables seen in the field relative to those in the laboratory (Kessler and Vesterlund 2015).

Table 3. Experimental Treatments

Experimental Session 1	Learning from a stranger for a quality-oriented product
Experimental Session 2	Learning from a stranger for a taste-oriented product
Experimental Session 3	Learning from a friend for a quality-oriented product
Experimental Session 4	Learning from a friend for a taste-oriented product

Our economic experiment has a 2x2 design: Corresponding to our analytical frameworks, we implement four experimental treatments (see Table 3) which involve manipulating the social “connectedness” of players (i.e., players are strangers or friends), as well as manipulating whether the product is quality-oriented or taste-oriented. There were four experimental sessions, and each session corresponded to one treatment. We recruited 320 undergraduate students from a large university, and randomly assigned them in one of four experimental sessions (treatments). In each session, we had 80 participants. The detailed experimental instructions are in online appendix B. Similar to the setup of the analytical framework, each player in the experiment was considering purchasing a product with both quality and taste uncertainty. The quality of the product can be high or low with probability ½ respectively. If the product quality is high, it is worth 100 tokens, and if the quality is low, it is worth 60 tokens. Each participant is a zero-type consumer, and the product can be a zero-type or one-type product with a probability 1/2, respectively. If the product is a zero-types product, then it fits her preference, otherwise it does not. At the beginning of the experiment, each participant was given 65 initial tokens (100 tokens = $10), which can be used to purchase the product. In our experiment, we set $V_H = 100$, $V_L = 60$, and $\alpha = 0.6$.

In experimental sessions 1 and 3 (quality-oriented product), the unmatched cost, r, is set to be 30, and in experimental sessions 2 and 4 (taste-oriented product), the unmatched cost, r, is set to be 50.[11] If a participant does not purchase the product, her final payoff in the experiment is 65 tokens. If a participant purchases the product, the net payoff from purchasing the product is given by equation (1). The price for the product in experimental session 1 is 65 tokens according to equation (2). A participant in experimental session 1 can use all her initial tokens to purchase the product. If the product is of high quality and matches her taste, according to equation (1), the participant will obtain the utility value, $V - r \cdot I_{\{unmatched\}} = V_H = 100$. In this case, her final payoff in the experiment is 100 tokens (greater than the initial 65 tokens, and the net gain from the transaction is 100 – 65 = 35 tokens). If the product is of low quality and does not match her taste, the participant will obtain the utility value, $V - r \cdot I_{\{unmatched\}} = V_L - r = 30$. In this case, her

[11] Later, we will see that these choices of r guarantee that $\frac{V_H}{r} > \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$ in the quality-oriented treatments, and $\frac{V_H}{r} < \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$ in the taste-oriented treatments.

final payoff in the experiment is 30 tokens (smaller than the initial 65 tokens, and the net loss from the transaction is 65 – 30 = 35 tokens).

Before each participant made a decision, she observed the decision of a previous player who had faced a similar decision making problem. Each participant was informed that the previous decision maker received a quality signal and a taste signal as described in our analytical model and made a rational decision. In the experiment, we set signal precision, $w = q = 0.75$. We ran experimental sessions 1 and 2 in which a player did not know the previous decision maker's type (a stranger), and sessions 3 and 4 in which a player knew the previous decision maker's type (a friend).

In each of our experimental sessions, we exogenously manipulated the decision of the previous decision maker to avoid confounding factors. In particular, in each experimental session, we randomly selected 40 participants and told them that the decision of the previous decision maker was to purchase the product. For the rest of 40 participants, they were told that the decision of the previous decision maker was not to purchase the product. Finally, we asked the choice of each participant.

In all of the treatments, the subjects participated in the experiment via the computer system that we developed. Throughout the experiment, the participants were not allowed to communicate in person and could not see others' screens. All the participants also finished a post-experiment survey on their demographic information.

4.2 Model-Free Evidence

We start our analysis by conducting univariate comparisons of the four treatments. We graphically describe the raw treatment effects and provide some univariate evidence in Figure 1.

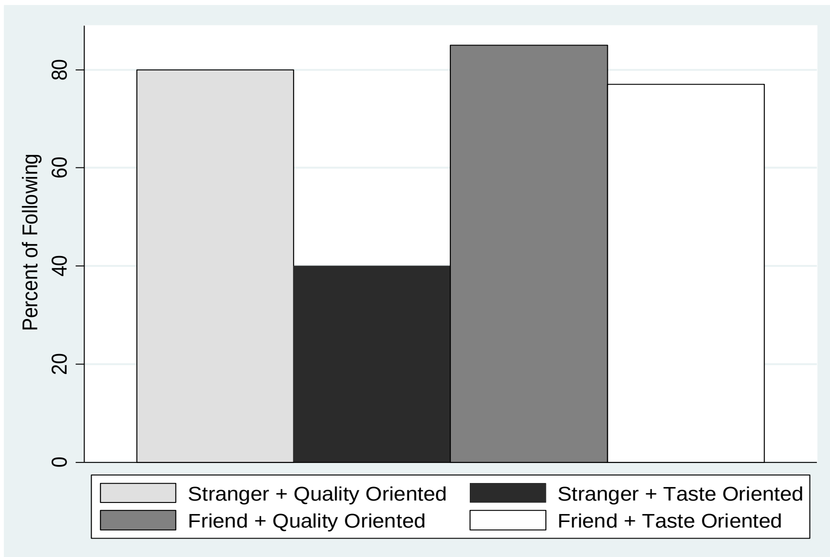

Figure 1. Comparisons of the Percent of Following in the Four Treatments

Figure 1 displays the percent of participants following the decision of the previous decision maker. First, we find that a participant is much more likely to follow the previous stranger's decision for quality-oriented product than for taste-oriented product: The percent of following in treatment 1 is significantly greater than that in treatment 2 (p value < 0.01), which provides support for H1. In addition, we find that a participant is very likely to follow the previous friend's decision regardless of whether the product is quality or taste oriented: The percent of following in treatment 3 is not significantly different from that in treatment 4 (p value > 0.1), which provides support for H2. Finally, the percent of following in treatment 4 is significantly greater than that in treatment 2 (p value < 0.01). This model-free result supports H3: For taste-oriented products, the effect of learning from friends is stronger than that of learning from strangers.

4.3 Empirical Framework and Results

We examine our hypotheses more rigorously in a regression framework. To test H1, we focus on the treatment of learning from a stranger (observations in experimental sessions 1 and 2) and estimate the following baseline linear probability model:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 (X_i \cdot Taste_i) + \varepsilon_i, \quad (3)$$

where the subscript i represents a participant in the treatment of learning from a stranger (experimental sessions 1 and 2), the dependent variable Y_i is a binary variable indicating whether participant i purchases the product (purchase: 1, not purchase: 0), X_i is a binary variable indicating the decision of the previous decision maker before participant i (purchase: 1, not purchase: 0), $Taste_i$ is a binary variable indicating whether the treatment is taste-oriented product (taste-oriented product: 1, quality-oriented product: 0), and ε_i is the random error. The linear probability model used in equation (3) is one of several widely used discrete choice models in the econometrics literature (Wooldridge 2002). Wooldridge (2002) states that the coefficients from the linear probability model can provide a good estimate near the average values of the covariates.[12]

Our estimation results are presented in Table 4. Column 1 shows the ordinary least squares (OLS) results. To alleviate concerns about the failure to meet standard regression assumptions such as clustering and heteroskedasticity, we compute the robust *t* statistics using the Huber–White sandwich estimators in column 1. In column 1, β_1 measures the impact of observational learning

[12] One weakness of the linear probability model is that the predicted probability (the fitted value) may not lie between 0 and 1. As Wooldridge emphasized (2002, p. 455): "Even with these weaknesses, the LPM (linear probability model) often seems to give good estimates of the partial effects on the response probability near the center of the distribution of **x**.… If the main purpose is to estimate the partial effect of x_j on the response probability, averaged across the distribution of **x**, then the fact that some predicted values are outside the unit interval may not be very important. The LPM need not provide very good estimates of partial effects at extreme values of **x**."

from a stranger for quality-oriented products, and $\beta_1 + \beta_2$ measures the impact of observational learning from a stranger for taste-oriented products. We find that β_1 is positive and statistically significant. It means that for quality-oriented products, if the prior decision maker (a stranger) purchases the product, participant i's purchase probability will increase by 25%, supporting the first part of H1. For taste-oriented products, the impact of observational learning from a stranger is $\beta_1 + \beta_2 = 0.25 - 0.1 = 0.15$. For $\beta_1 + \beta_2$, we conduct a t-test and find that $\beta_1 + \beta_2$ is not significantly different from 0 (p value > 0.1). It implies that for taste-oriented products, the impact of observational learning from a stranger is not significant, supporting the second part of H1. The coefficient on the interaction term, $X_i \cdot Taste_i$, is significantly negative, suggesting the effect of learning from strangers is stronger for quality-oriented products than for taste-oriented product.

Table 4. The Effect of Observational Learning from Strangers: Testing H1

VARIABLES	(1) OLS	(2) Bootstrapping	(3) Logit
X_i	0.250***	0.250***	1.048**
	[2.711]	[2.726]	[2.537]
$X_i \cdot Taste_i$	-0.100**	-0.100**	-0.442**
	[-2.236]	[-2.354]	[-2.116]
Constant	0.450***	0.450***	-0.201
	[8.014]	[8.055]	[-0.890]
Observations	160	160	160

Robust z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

A potential issue in the estimation is the small sample size in our setup, which is a common problem for laboratory experimental methods. Since the validity of t-statistics depends on the asymptotic distribution of large samples, bootstrapping is useful for estimating the distribution of a statistic without resorting to asymptotic properties, and is particularly useful when the sample size is insufficient for straightforward statistical inference. Therefore, we use bootstrapping to compute the standard errors. Specifically, we draw a sample with replacement, and repeat this process 10,000 times to compute the bootstrapped standard errors. As can be seen in column 2 of Table 4, our results are robust. One weakness of our baseline linear probability model is that the predicted probability (the fitted value) may not lie between 0 and 1, so we also conduct a logit regression in column 3 of Table 4. The results are consistent: Roughly speaking, the logit estimates should be divided by four to compare them with the linear probability model estimates (Wooldridge 2002).

To examine our H2, we focus on the treatment of learning from a friend (observations in experimental sessions 3 and 4) and re-estimate regression equation (3). In Table 5, we present our estimation results for learning from a friend. Similarly, in column 1 of Table 5, β_1 measures the impact of observational learning from a friend for quality-oriented products, and $\beta_1 + \beta_2$ measures the impact of observational learning from a friend for taste-oriented products. We find that the coefficient, β_1, is positive and statistically significant. It means that for quality-oriented products, if the prior decision maker (a friend) purchases the product, participant *i*'s purchase probability will increase by 68.8%. For taste-oriented products, the impact of observational learning from a stranger is $\beta_1 + \beta_2 = 0.688 - 0.125 = 0.563$. For $\beta_1 + \beta_2$, we conduct a *t*-test and find that $\beta_1 + \beta_2$ is significantly greater than 0 (p value < 0.001). It implies that for taste-oriented products, the impact of observational learning from a friend is also significant. Therefore, H2 is supported. We also use bootstrapping to compute the standard errors in column 2 of Table 5 and conduct a logit regression in column 3 of Table 5. The results are robust.

Table 5. The Effect of Observational Learning from Friends: Testing H2

VARIABLES	(1) OLS	(2) Bootstrapping	(3) Logit
X_i	0.688***	0.688***	3.507***
	[10.34]	[10.46]	[5.889]
$X_i \cdot Taste_i$	-0.125	-0.125	-0.960
	[-1.523]	[-1.521]	[-1.475]
Constant	0.213***	0.213***	-1.310***
	[4.602]	[4.666]	[-4.778]
Observations	160	160	160

Robust z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

To investigate H3(i), we focus on the treatment of social ties for taste-oriented products (observations in experimental sessions 2 and 4) and estimate the following regression equation:

$$Y_i = \gamma_0 + \gamma_1 X_i + \gamma_2 (X_i \cdot Friend_i) + \varepsilon_i, \tag{4}$$

where $Friend_i$ is a binary variable indicating whether the treatment is observational learning from a friend (learning from a friend: 1, learning from a stranger: 0).

We present the estimation results in Table 6. In column 1 of Table 6, γ_1 measures the impact of observational learning from a stranger for taste-oriented products, $\gamma_1 + \gamma_2$ measures the impact of observational learning from a friend for taste-oriented products, and γ_2 quantifies the difference between the magnitudes of these two learning effects. We find that γ_1 is not statistically significant, which suggests that the impact of observational learning from a stranger for taste-oriented products is not significant. We also conduct a *t*-test and find that $\gamma_1 + \gamma_2$ is significantly different from zero (p value < 0.001), which indicates that the impact of observational learning from a friend for taste-oriented products is significant. A positive and significant γ_2 supports H3(i): For taste-oriented products, the effect of learning from friends is stronger than that of learning from strangers. Our results are robust when we use bootstrapping in column 2 of Table 6 and conduct a logit regression in column 3 of Table 6.

Table 6. The Effect of Observational Learning from Friends: Testing H3(i)

VARIABLES	(1) OLS	(2) Bootstrapping	(3) Logit
X_i	0.0875	0.0875	0.355
	[0.907]	[0.925]	[0.902]
$X_i \cdot Friend_i$	0.175***	0.175***	0.831***
	[3.703]	[3.723]	[3.666]
Constant	0.512***	0.512***	0.0500
	[9.084]	[9.258]	[0.223]
Observations	160	160	160

Robust z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

To investigate H3(ii), we focus on the treatment of social ties for quality-oriented products (observations in experimental sessions 1 and 3) and re-estimate regression equation (4). The results are presented in Table 7. We find that the coefficients on the interaction term, $X_i \cdot Friend_i$, is not significant, which suggests that the effect of learning from friends is similar to that from strangers for quality-oriented products and supports H3(ii).

Table 7. The Effect of Observational Learning from Friends: Testing H3(ii)

VARIABLES	(1) OLS	(2) Bootstrapping	(3) Logit
X_i	0.550***	0.550***	2.582***
	[6.586]	[5.426]	[5.524]
$X_i \cdot Friend_i$	0.200	0.200	1.350
	[1.288]	[1.102]	[1.136]
Constant	0.150***	0.150***	-1.735***
	[3.722]	[3.226]	[-5.523]
Observations	160	160	160

Robust z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

In summary, our experimental results show that all the hypotheses are supported. These results provide evidence for the propositions stemming from our analytical framework. Note that these propositions are typically difficult to empirically validate using archive data (observational data) due to the common external stimuli of friends. For example, friends are more likely to see the same advertisements, which can confound the estimated effect of observation learning. In our experimental setting, we thus focus on assessing internal validity in a controlled laboratory setting.

5 Experimental Study 2

5.1 Experimental Design and Summary Statistics

A limitation of experimental study 1 is that in the treatment of learning from friends, a participant has no real social connections with the previous decision maker. It is difficult to envision a laboratory experiment that can fully mirror the circumstances of the external environment of interest. In particular, an exogenous type matching process in our analytical framework may not capture closeness and intimacy in friendships in the field (Parks and Floyd 1996). In this study, we conduct an experiment with more field elements to address this issue of artificial friendships. Specifically, we use data from the Facebook API to measure social ties that connect our subjects with each other. By looking at socially networked peers, rather than conducting the experiment with artificial friendships, an increase in external validity is the focus.

The focal issue of interest in this experiment is H3(i) i.e., the effect of social ties on the magnitude of observational learning for horizontally differentiated products. Recall that in experimental study 1, the measure of social ties is an exogenous binary variable: The previous decision maker is either a friend or a stranger. If the previous decision maker is a friend, then her type is known to the participant, otherwise her type is unknown. This type matching process could be viewed as overly-simplistic since it does not capture many important aspects of social ties. In experimental study 2, we propose three continuous measures to quantify the strength of social ties. We want to test a continuous version of H3(i) which is:

If the social tie between a participant and the previous decision maker is stronger, the effect of observational learning for horizontally differentiated products is larger.

In study 2, participants were recruited via an initial email asking that any interested parties sign up for our Facebook application. This initial list of email addresses was obtained from undergraduate and graduate students, as well as from staff and co-workers, at a large university. Our subject pool consisted of 200 people who had Facebook accounts. We made sure that these subjects did not participate in our study 1. When subjects signed up for our experiment and agreed to participate they granted us access to their Facebook wall. This meant that we were able to use individuals' data to characterize the social ties, between a participant and the previous decision maker before her, using well validated proxies (Bapna et al. 2017a, b). These tie strength measures are:

- $Embeddedness_{s,r}$ = (number of common friends)$_{s,r}$/min (k_s - 1, k_r - 1), where k_s and k_r are the network degree of the participant and the previous decision maker before her respectively.[13]

[13] We also use another definition: $Embeddedness_{s,r}$ = (number of common friends)$_{s,r}$/ (k_s + k_r), and the empirical results are similar.

- *PhotosTagged* = total number of photos in which they are tagged together,
- *SharedWallposts* = total number of times they post on the others' wall.

In study 2, the treatment was that we randomly paired each participant with one of her Facebook friend (the previous decision maker). Therefore, we could compute the three tie strength measures for these 200 pairs. The summary statistics are presented in Table 8. Each participant was given a decision scenario, whether to dine at a restaurant. We chose restaurant dining as the specific decision scenario in study 2 because it is taste oriented.

Table 8. Summary Statistics of Tie Strength Measures

VARIABLES	Mean	Std Dev	Median
PhotosTagged	3.12	5.84	1
SharedWallposts	2.27	4.93	2
Embeddedness	0.13	0.39	0.15

In this decision scenario, each participant was informed that her paired Facebook friend had made a choice: whether to dine at a restaurant or not. If her friend dine at the restaurant, she can observe her friend's electronic check-in on Facebook (see Figure 2).

Then, like study 1, we exogenously manipulated the decision of the previous decision maker. In particular, we randomly selected 100 participants and told them that the decision of the previous decision maker: is to dine at the restaurant. For the rest of 100 participants, they were told that the decision of the previous decision maker: is not to dine at the restaurant. Finally, we ask the choice of each participant.

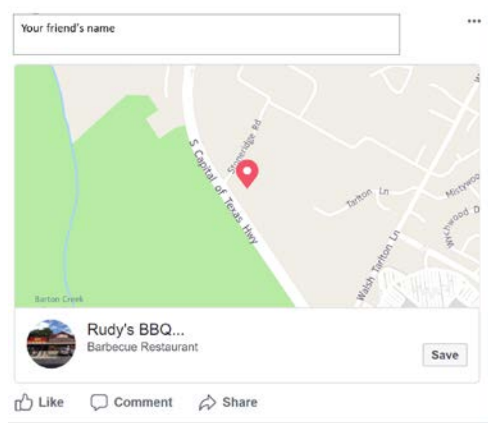

Figure 2. An Electronic Check-in at a Restaurant

5.2 Experimental Results

To investigate the continuous version of H3, we estimate the following regression equation:

$$Y_i = \delta_0 + \delta_1 X_i + \delta_2 (X_i \cdot Embeddedness_i) + \delta_3 (X_i \cdot PhotosTagged_i) + \delta_4 (X_i \cdot SharedWallposts_i) + \varepsilon_i, \quad (5)$$

where $Embeddedness_i$, $PhotosTagged_i$, $SharedWallposts_i$ are the three tie strength measures.

We present the estimation results in Table 9. In column 1 of Table 9, δ_2 quantifies the impact of the first tie strength measure, embeddedness (shared friends), on the learning effect, δ_3 quantifies the impact of the second tie strength measure, tagged photos, on the learning effect, and δ_4 quantifies the impact of the third tie strength measure, shared wall posts, on the learning effect.

We find that δ_2, δ_3, and δ_4 are positive and statistically significant, which supports the continuous version of H3: For taste-oriented products, the effect of learning from friends increases with the strength of social ties. A standard-deviation increase in embeddedness makes a participant 6.1 percent (15.7*0.39, 0.39 is the standard deviation of embeddedness in Table 8) more likely to follow the decision of the previous decision maker. A standard-deviation increase in tagged photos makes a participant 34.1 percent (5.32*5.84, 5.84 is the standard deviation of tagged photos in Table 8) more likely to follow the decision of the previous decision maker. A standard-deviation increase in shared wall posts makes a participant 20.3 percent (4.12*4.93, 4.93 is the standard deviation of shared wall posts in Table 9) more likely to follow the decision of the previous decision maker. Our results are robust when we use bootstrapping in column 2 of Table 9 and conduct a logit regression in column 3 of Table 9.

Table 9. The Effect of Observational Learning under Different Social Ties

VARIABLES	(1) OLS	(2) Bootstrapping	(3) Logit
X_i	0.0612	0.0612	0.236
	[0.436]	[0.418]	[0.721]
$X_i \cdot Embeddedness_i$	0.157***	0.157***	0.427***
	[3.347]	[3.283]	[3.587]
$X_i \cdot PhotosTagged_i$	0.0532***	0.0532***	0.273***
	[4.547]	[4.326]	[4.739]
$X_i \cdot SharedWallposts_i$	0.0412***	0.0412***	0.187***
	[3.586]	[3.634]	[3.827]
Observations	200	200	200

Robust z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

Gee et al. (2017) proposed two categories of tie strength measures: “contact-based” measures and “structure-based” measures. Contact-based tie strength records the number of interactions between an individual and a friend. Our tagged photos and shared wall posts belong to contact-based tie strength measures. In contrast, structure-based measures use the structure of the network to model tie strength and capture the idea of bridging across different groups. Our embeddedness (shared common friends) is a structure-based tie strength measure. According to our estimation results, the role of embeddedness is much smaller than that of tagged photos and shared wall posts, suggesting that contact-based tie strength is more important than structure-based tie strength in accelerating observational learning. The intuition behind this result is as follows: Contact based measures (like shared wall posts and tagged photos) indicate stronger ties between friends as compared to structure based measures (like common friends). Due to this, the effect of learning is larger between friends for contact based measures versus structure based measure.

6. Discussion and Conclusions

In this study, we investigate multi-dimensional observational learning by allowing consumers to learn from both quality and taste dimensions. In an analytical model, we show how product differentiation interacts with social ties in the context of observational learning. We also provide experimental evidence for the interaction effects derived from our theoretical framework. Our study fills an important gap in the literature by providing a deep understanding of the interaction between product differentiation and social ties in multi-dimensional observational learning.

The prevalence of social sharing has provided an unprecedented opportunity for online retailers to engineer observational learning in order to increase sales. For example, Kohl's (a department store) has a social gallery, which displays posts on its products from both Twitter and Instagram and allows consumers to purchase via direct links to product home page.[14] This feature enables potential consumers to learn about the product by observing purchase decisions of others. Thus, understanding how product differentiation and social ties moderate observational learning

[14] See https://www.kohls.com/feature/kohls-social-gallery.jsp (last accessed: May 28, 2018).

helps retailers target influential consumers.

Our research sheds light on how retailers should increase observational learning for different types of products. For horizontally differentiated products, we find that the effect of learning from friends is larger than that from strangers. However, for vertically differentiated products, the effect of learning from friends is similar to that from strangers. Thus, retailers with marketing budgets offering horizontally differentiated products (like apparel with different colors or food products with different flavors) have greater incentives to cooperate with social media platforms (e.g. Instagram and Pinterest) in targeting influential customers (Huang et al. 2018). For example, after finishing an online transaction, online retailers can encourage influential customers of such products to share their purchases via social media through a discount scheme (the discount scheme can be a simple percent discount or be based on consumer contests, see Liu et al. 2007). Thus, for horizontally differentiated products, purchases by influential customers can lead to significantly higher observational learning effects.

We also provide practical insights for retailers on how to identify influential customers in social networks and use strong social ties to boost observational learning. Through experimental study 2, we find that for horizontally differentiated products, the effect of learning from friends increases with the strength of social ties. By forming alliances with social networks, retailers can target consumers based on the tie strength measures: embeddedness (shared friends), tagged photos, and shared wall posts. The result that contact-based tie strength (i.e., networks connecting users through tagged posts and photos) is more important than structure-based tie strength (i.e., networks connecting users through shared friends) in accelerating observational learning is also important in choosing among different social networks.

Future research directions to pursue are as follows. It would be interesting to empirically examine (and thus, provide some external validity) the role of network structures in multi-dimensional observational learning. Considering the interaction between word of mouth (learning from others' comments) and observational learning (learning from others' actions) in the context of multi-dimensional observational learning (Chen et al. 2011, Susarla et al. 2016, Li and Wu 2018) would be another potential extension of our results.

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Online Appendix

Multi-Dimensional Observational Learning in Social Networks: Theory and Experimental Evidence

Online Appendix A: Proof

Proof of Lemma 1

Proof: (1) If consumer *j* receives signals S_H and S_0, her expected payoff is given by

$$\mathbb{E}\left[u_j|I_j\right] = \mathbb{E}[V|S_H] - r \cdot \mathbb{E}\left[I_{\{unmatched\}}|S_0\right] - \frac{1+\alpha}{2}V_H + \frac{1}{2}r,$$

where I_j is consumer *j*'s information set, $\mathbb{E}[V|S_H] = qV_H + (1-q)V_L = (q + \alpha - \alpha q)V_H$, and $\mathbb{E}\left[I_{\{unmatched\}}|S_0\right] = 1 - w$. Therefore,

$$\mathbb{E}\left[u_j|I_j\right] = (1-\alpha)\left(q - \frac{1}{2}\right)V_H - \left(\frac{1}{2} - w\right)r > 0.$$

The inequality holds because $0 < \alpha < 1$, $q > \frac{1}{2}$, and $w > \frac{1}{2}$. Therefore, consumer *j* will always purchase the product.

(2) If consumer *j* receives signals S_L and S_1, her expected payoff is given by

$$\mathbb{E}\left[u_j|I_j\right] = \mathbb{E}[V|S_L] - r \cdot \mathbb{E}\left[I_{\{unmatched\}}|S_1\right] - \frac{1+\alpha}{2}V_H + \frac{1}{2}r,$$

where $\mathbb{E}[V|S_L] = qV_L + (1-q)V_H = (1 - q + \alpha q)V_H$, and $\mathbb{E}\left[I_{\{unmatched\}}|S_1\right] = w$. Therefore,

$$\mathbb{E}\left[u_j|I_j\right] = (1-\alpha)\left(\frac{1}{2} - q\right)V_H - \left(w - \frac{1}{2}\right)r < 0.$$

The inequality holds because $0 < \alpha < 1$, $q > \frac{1}{2}$, and $w > \frac{1}{2}$. Therefore, consumer j will not purchase the product.

(3) If consumer j receives signals S_H and S_1, her expected payoff is given by

$$\mathbb{E}[u_j|I_j] = \mathbb{E}[V|S_H] - r \cdot \mathbb{E}[I_{\{unmatched\}}|S_1] - \frac{1+\alpha}{2}V_H + \frac{1}{2}r,$$

where $\mathbb{E}[V|S_H] = qV_H + (1-q)V_L = (q + \alpha - \alpha q)V_H$, and $\mathbb{E}[I_{\{unmatched\}}|S_1] = w$. Therefore,

$$\mathbb{E}[u_j|I_j] = (1-\alpha)\left(q - \frac{1}{2}\right)V_H - \left(w - \frac{1}{2}\right)r.$$

Hence, $\mathbb{E}[u_j|I_j] > 0$ if $\frac{V_H}{r} > \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$.

(4) If consumer j receives signals S_L and S_0, her expected payoff is given by

$$\mathbb{E}[u_j|I_j] = \mathbb{E}[V|S_L] - r \cdot \mathbb{E}[I_{\{unmatched\}}|S_0] - \frac{1+\alpha}{2}V_H + \frac{1}{2}r,$$

where $\mathbb{E}[V|S_L] = qV_L + (1-q)V_H = (1 - q + \alpha q)V_H$, and $\mathbb{E}[I_{\{unmatched\}}|S_0] = 1 - w$. Therefore,

$$\mathbb{E}[u_j|I_j] = (1-\alpha)\left(\frac{1}{2} - q\right)V_H - \left(\frac{1}{2} - w\right)r.$$

Hence, $\mathbb{E}[u_j|I_j] > 0$ if $\frac{V_H}{r} < \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$. ■

Proof of Proposition 1

Proof: According to Lemma 1, if consumer *j* purchases the product when $\frac{V_H}{r} > \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$, consumer *i* will infer that consumer *j* either receives signals S_H and S_0 or receives S_H and S_1 (note that consumer *i* does not know consumer *j*'s type). The expected payoff of consumer *i* is given by:

$$\mathbb{E}[u_i|I_i] = \mathbb{E}[V|S_H] - r \cdot \mathbb{E}\left[I_{\{unmatched\}}\right] - \frac{1+\alpha}{2} V_H + \frac{1}{2} r,$$

where $\mathbb{E}[V|S_H] = qV_H + (1-q)V_L = (q + \alpha - \alpha q)V_H$, and $\mathbb{E}\left[I_{\{unmatched\}}\right] = \frac{1}{2}$. Therefore,

$$\mathbb{E}[u_i|I_i] = (1-\alpha)\left(q - \frac{1}{2}\right) V_H > 0.$$

If consumer *j* does not purchase the product when $\frac{V_H}{r} > \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$, consumer *i* will infer that consumer *j* either receives signals S_L and S_0 or receives S_L and S_1. The expected payoff of consumer *i* is given by:

$$\mathbb{E}[u_i|I_i] = \mathbb{E}[V|S_L] - r \cdot \mathbb{E}\left[I_{\{unmatched\}}\right] - \frac{1+\alpha}{2} V_H + \frac{1}{2} r,$$

where $\mathbb{E}[V|S_L] = qV_L + (1-q)V_H = (1 - q + \alpha q)V_H$, and $\mathbb{E}\left[I_{\{unmatched\}}\right] = \frac{1}{2}$. Therefore,

$$\mathbb{E}[u_i|I_i] = (1-\alpha)\left(\frac{1}{2} - q\right) V_H < 0. \blacksquare$$

Proof of Proposition 2

Proof: According to Lemma 1, if consumer *j* purchases the product when $\frac{V_H}{r} < \frac{w-\frac{1}{2}}{(1-\alpha)\left(q-\frac{1}{2}\right)}$, consumer *i* will infer that (i) consumer *j* receives signals S_H and S_1 or (ii) receives S_L and S_1, or (iii) receives signals S_H and S_0, or (iv) receives S_L and S_0. Note that consumer *i* does not know consumer *j*'s type. Therefore, although consumer *i* knows that consumer *j*'s taste is matched (because consumer *j* purchases the taste-oriented product), she is not sure about consumer *j*'s taste signal. As a result, consumer *i* does not receive any new information and learns nothing from consumer *j*'s decision: Consumer *i* is not sure about consumer *j*'s quality and taste signals.

Therefore, consumer *i* can use only her prior information, and the expected payoff of consumer *i* is given by:

$$\mathbb{E}[u_i] = \mathbb{E}[V] - r \cdot \mathbb{E}\left[I_{\{unmatched\}}\right] - \frac{1+\alpha}{2}V_H + \frac{1}{2}r = 0.$$

It implies that consumer *i* will be indifferent between purchasing and not purchasing the product.

■

Proof of Proposition 3

Proof: Consumer *i* knows that she has the same type as consumer *k*. The only difference is that consumer *k* has additional private quality and taste signals. Given that both consumers *i* and *k* are rational, if consumer *i* observes consumer *k*'s private quality and taste signals, she will make the same decision as that of consumer *k*. ■

Online Appendix B: Experimental Instructions for Study 1

The experimental instructions for session 1 are shown as follows. The guidelines for other sessions are similar.

Experiment Guidelines

General Guideline: This is an economic experiment so it is conducted with Real Money (100 tokens = $10)! Your profit is a direct result of your performance during the experiment.

Experiment Description

Consider that you want to purchase a product. You are initially assigned 65 tokens.

Product quality: The quality of the product can be high or low with a probability ½, respectively. If the product quality is high, it is worth 100 tokens, and if the quality is low, it is worth 60 tokens.

Product fitness: You are a zero-type consumer, and the product can be a zero-type or one-type product with a probability 1/2, respectively. If the product is a zero-types product, then we call this product fits your preference, otherwise it does not fit your preference.

Your final payoff depends on both product quality and product fitness. If you choose not to buy the product, you will get 65 tokens. If you choose to buy the product, there are four scenarios:

1. If the product quality is high and it fits your preference, then you will get 100 tokens.
2. If the product quality is high and it does not fit your preference, then you will get 100 – 30 = 70 tokens.
3. If the product quality is low and it fits your preference, then you will get 60 tokens.
4. If the product quality is low and it does not fit your preference, then you will get 60 – 30 =

30 tokens.

Your information: You observe the purchase decision of a stranger. The stranger can be a zero-type or one-type consumer with a probability ½, respectively. The stranger has faced a similar decision-making problem and received a quality signal and a taste signal. The quality signal can be either a high or low signal: If the product quality is high, the probability of receiving a high signal is 3/4, and if the product quality is low, the probability of receiving a low signal is ¼. The taste signal can be either a zero-type or one-type signal: If it is a zero-type product, the probability of receiving a zero-type signal is 3/4, and if it is a one-type product, the probability of receiving a one-type signal is ¼. The stranger knows these two signals, but you don't know. What you know is that the stranger has purchased the product.

After reading the guidelines, you need to make a decision about whether to purchase the product.