Escaping the Herd: Experimental Evidence on the Need to Be Different in Social Networks*

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Abstract

We explore how people trade off their needs to belong and to be different by first developing an analytical model and then testing its predictions through a large-scale field experiment on a leading social networking site in China. Our experimental design allows us to focus on the two fundamental needs by minimizing confounding factors such as pre-existing taste similarities between a subject and her friends, signalling of one’s social identity, and observational learning. Contrary to the popular belief that people tend to follow others’ choices, subjects in our experiment are more likely to diverge from the popular choice among their friends as the adoption rate of that choice increases. Unless adoption is near unanimity, divergence becomes even more pronounced when subjects are reminded that their choices are visible to their friends. For robustness, we replicate these findings on Amazon Mechanical Turk in the United States. As our study shows that the need to be different can dominate the need to be belong in certain contexts, we discuss managerial implications of our results for product diffusion and social media marketing.

Keywords: social influence, product diffusion, social media marketing
1 Introduction

Social media ad spending has been growing at a lightening speed in recent years. Industry 
reports show that 86% of marketers believe social media is important for their businesses,\(^1\) 
and 93% of marketers plan to maintain or increase social media ad spending in 2014.\(^2\) In 
total, the U.S. social media ad spending is estimated to grow from $4.7 billion in 2012 to 
$11 billion in 2017, representing an annual growth rate of 18.6%.\(^3\)

The common belief behind social media marketing is the idea of information cascade: An 
information cascade occurs when it is optimal for an individual, having observed the actions 
of those ahead of him, to follow the behavior of the preceding individual without regard to 
his own information (Bikhchandani et al. 1992). This belief sets social media marketing apart 
from traditional marketing, as the standard STP (segmentation, targeting and positioning) 
strategies rarely involve taking advantage of people’s social relationships (Trusov et al. 2009).

Social networking platforms heavily rely on this belief when explaining why advertisers 
should work with them and how such advertising works (e.g., “When people interact with 
the content on your page, their friends are eligible to see the activity. When people do 
things such as like, comment or check-in to your page, you can promote those activities to 
their friends.”).\(^4\) They also try to leverage herding to increase engagement. Facebook, for 
extample, displays information on games a user’s friends play in the hope of getting the user 
to start playing the same games. In fact, the belief is so strong that Facebook launched 
its Beacon service in 2007 with 44 partner websites, which sent data from these sites to 
Facebook, for the purpose of allowing users to share their activities with their friends to 
achieve better advertising targeting.\(^5\)

Consistent with the strong herding sentiment in the industry, academic research in mar-
keting, economics and psychology has shown consistent evidence that people tend to mimic 
others’ choices. Asch (1956), in his seminal paper, documents how individuals often succumb 
to peer pressure when making judgements. More recently, Cai et al. (2009) and Zhang (2010), 
among others, find empirical evidence for “observational learning” as described in a sequen-

\(^{1}\)Source: http://www.socialmediaexaminer.com/SocialMediaMarketingIndustryReport2013.pdf, 
accessed May 2014.

\(^{2}\)See a breakdown of marketers’ planned changes in ad spending at http://www.emarketer.com/

\(^{3}\)Source: http://www.biakelsey.com/Company/Press-Releases/130410-U.S. 


tial decision model in Banerjee (1992). The central idea behind the herding phenomena is that people update their beliefs on the “quality” of different alternatives through observing others’ decisions on these alternatives, thinking that “they may know something that I do not know.” In some cases, the inference and updating can be so strong that it overshadows one’s own private information and leads to a decision outcome that is similar to others’ and opposite to the one that would have been chosen in the absence of such observations.

Despite strong industry advocates and increasing scholarly interest (e.g., Yoganarasimhan 2012), social media has not yet proven to be effective at yielding high returns. As summarized in the industry report mentioned above, only 37% of marketers think that their Facebook efforts are effective. At the same time, a significant 89% of marketers state that increased exposure instead of social influence is the number-one benefit of social media marketing, a benefit that, in fact, is quite similar to that of traditional marketing.

In this paper, we revisit the popular belief that people like to mimic others, in particular, their friends. We argue that we have long known that humans need to be ‘different’ (e.g., Snyder and Fromkin 1980), and there is no reason to believe that this need would always be subordinate to the need to fit into a wider social group. To gain a deeper understanding of the tradeoff between people’s needs to be different and to belong, we first build an analytical model to allow the strengths of these two needs to change with the adoption rate of the most popular choice in one’s social circle. We then develop hypotheses from our model and test them in a large-scale experiment in a field setting.

There are two important reasons why there exists little empirical evidence on the tradeoff between these two fundamental and yet opposing human needs. First, interpersonal relationships are subtle and hard to observe. People may be unwilling or unable to clearly define their relationships with others to the researcher.

Second, even when researchers have the opportunity to observe social relationships, there are a few external factors that can confound their ability to observe the tradeoff between the needs to belong and to be different. For example, it can be difficult to differentiate interpersonal influence from pre-existing taste similarities (e.g., Manski 1993, 2000; Hartmann et al. 2008). Also, in many social contexts, people are observed by not only their friends, but also ‘outsiders’ – a waiter or bartender, a shop assistant, or the wider general public (e.g., Ariely and Levav 2000; Berger and Heath 2008). As a result, they may choose to either conform or diverge in order to communicate a desirable social identity to out-group members. Finally, one needs to minimize the possibility of observational learning, which leads to herding as a resolution of uncertainty about different alternatives, rather than from the need to belong.
to a particular social group.

With the presence of such confounding factors, prior findings on behavioral convergence tend to reflect a combination of both internal and external factors rather than the tradeoff between the two underlying needs that we are trying to focus on.

In this paper, we use a large-scale field experiment to explore this tradeoff. The setting of our experiment is a leading social-networking website in China, Kaixin001.com (referred to as Kaixin henceforth). Users on Kaixin typically register with their real names and they have to mutually agree to a friendship for the site to acknowledge the connection. Our field experiment setting therefore eliminates (1) the assignment of subjects into an artificial social network, or (2) the need for subjects to imagine artificial friendship before making their choices.

In the experiment, we inform the participants of a randomly generated choice of virtual wall colors that we tell them is the ‘most popular,’ either among their friends or among all users on the site. We also display a randomly generated adoption rate of the popular color to each participant. Finally, for some participants, we display a “social message” to remind them that their choices are visible to their friends.

Our experimental design enables us to focus on how participants trade off their needs to belong and to be different by minimizing the aforementioned confounding factors. First, pre-existing (dis)similarity in friends’ tastes plays little role in our experiment. As both the popular color and its adoption rate among their friends or other users are randomly generated, any correlation between friends’ tastes can hardly be the driving force of either their convergence or divergence. Second, by Kaixin’s design, a user’s virtual house can be seen only by his friends on the site. That is, other users on the site cannot see the house. The “private-party” feature of the experiment alleviates the participants’ concern of establishing their group identity for out-group members, since they are not being observed by the general public. Finally, observational learning is minimized because the colors are standard and participants have the option to immediately see how each color looks on the wall before finalizing their choices.

We record the participants’ color choices before and after they see our experimental messages, and analyze how the overall likelihood of convergence changes with their knowledge of friends’ or all users’ adoption rates. Further, we also investigate whether the additional ‘nudging’ toward convergence offered by the social message, would indeed induce more con-
Our findings stand in stark contrast to previous findings on behavioral convergence: our subjects are more likely to diverge from the choice that (they are told) is popular among their friends as the popularity of that choice increases. In addition, we find that divergence usually becomes even more pronounced when subjects are reminded that their choices were visible to their friends. Unless adoption of the popular choice is near unanimity, in which case the social message indeed makes the final non-adopters more likely to adopt, we find that pushing for convergence by reminding users about the visibility of their choices generally tends to backfire. Besides these main results, we also find that female participants, participants born in more affluent regions, and those who live outside China have a stronger need to be different from their friends.

Our results suggest that once we eliminate contextual influences, the need to be different can dominate the need to follow one’s friends’ tastes. The results also have interesting implications on how people can enjoy being different but at the same time seem to prefer to hide such difference from their friends. In particular, when the adoption rate of a popular choice is high but not near unanimity, people tend to enjoy both being different and showing their ability to be so to their friends. When adoption is nearly unanimous, however, people still enjoy being different but prefer to hide this difference from their friends.

While behavioral divergence is more striking in conformity-driven cultures such as China, we believe that the results would hold in western cultures as well. We replicate the study in the U.S. in the form of a survey experiment on Amazon Mechanical Turk (MTurk henceforth).\(^8\) The experimental design is identical to our study in China, except that the participants are from the U.S. and are asked to think of hypothetic scenarios in which a certain fraction of their Facebook friends, or all Facebook users, choose a certain wall color. The results from MTurk are similar to those from our field experiment on Kaixin and confirm our intuition on the prevalence of behavioral divergence.

\subsection*{1.1 Related Literature}

Our paper contributes to the emerging literature on product diffusion in social networks. In particular, we focus on the direction of influence among members of the network. \(^9\)

\(^8\)See a description of MTurk at \url{http://en.wikipedia.org/wiki/Amazon_Mechanical_Turk}.

\(^9\)To maintain our focus, we abstract away from important questions such as how relationships are formed (e.g., Ansari et al. 2011) and how to identify the most “influential” users (e.g., Watts and Dodds 2007; Van den Bulte and Joshi 2007; Katona et al. 2011; Iyengar et al. 2011; Libai et al. 2013).
Influence among network members is typically initiated by word of mouth (WOM), observations of others’ choices, or both. Recent studies in marketing have explored many different aspects of WOM such as how to measure it (e.g., Godes and Mayzlin 2004), its impact on adoption and sales (e.g., Chevalier and Mayzlin 2006; Chen and Xie 2008; Trusov et al. 2009), and its dynamics (e.g., Godes and Silva 2012), motivation (e.g., Ying et al. 2006; Moe and Schweidel 2012) and manipulation (e.g., Anderson and Simester 2014; Mayzlin et al. forthcoming). In general, findings from this stream of the literature suggest that WOM is an important element in the modern marketing mix (Chen and Xie 2008), with positive online ratings boosting products’ online sales (Chevalier and Mayzlin 2006). Furthermore, WOM can be more effective than traditional marketing actions (Trusov et al. 2009), and the ability of seeding information with carefully selected users can further enhance the effectiveness of WOM marketing campaigns (Libai et al. 2013). Similar to the spirit of this paper, Moe and Schweidel (2012) find that while less frequent posters of online ratings exhibit bandwagon behavior, more active customers reveal differentiation behavior. In particular, when a product’s customers are polarized, posted opinions are more negative as a result of “activist” customers posting increasingly negative opinions in an effort to differentiate themselves from others in the community. While both our paper and their emphasize people’s incentive to appear different from others, they look at the dynamics in ratings of products of uncertain quality while we examine people’s choice among alternatives that are associated with minimum quality uncertainty.

More broadly speaking, while the general goal of this paper is to gain a deeper understanding of interpersonal influences in social networks, the design of our model and experiment is tailored for investigating influence that is initiated by observing others’ choices. This type of influence has also received considerable attention in the literature. Among the earliest studies, Deutsch and Gerard (1955) attribute the well known behavior shifts in group settings (Asch 1955) to either updating of beliefs or adherence to norms.

When there is uncertainty and belief updating in decision making, Kahneman and Tversky (1979); Scharfstein and Stein (1990); Banerjee (1992) and Bikhchandani et al. (1992) formulate theories on information cascade and observational learning. They find conditions under which it is optimal for individuals to imitate the behavior of others and disregard their own private information. Graham (1999); Çelen and Kariv (2004); Cipriani and Guarino (2005); Cai et al. (2009) and Zhang (2010) offer empirical evidence for observational learning. In general, if other individuals have superior information, imitation is likely to be useful to reduce uncertainty.
When belief updating and uncertainty is minimized, normative social influence is likely to emerge as a dominant driver of interpersonal dynamics in social networks. Existing research finds empirical evidence that individuals often conform to the behavior of others (e.g., Charness et al. 2007) because of peer pressure (e.g., Austen-Smith and Roland G. Fryer 2005; Mas and Moretti 2009) or the need to be consistent with their social (e.g., Benjamin et al. 2010) or group identities (e.g., Chen and Li 2009; Goette et al. 2006, 2012). As a result, social contagion can complement marketing communication and speed up product adoption (e.g., Manchanda et al. 2008; Iyengar et al. 2011; Toubia et al. forthcoming).

The need to be different, on the other hand, is discussed in the seminal work by Snyder and Fromkin (1980) and Brewer (1991), and could potentially drive individuals to diverge from others’ choices. There is little research on how this need is traded off against the need to belong, which is the main motivation of the current paper. One notable exception is Ariely and Levav (2000), who find evidence for group-level variety seeking in the context of lunch orders, beer sampling and wine tasting. Both their papers and ours highlight the finding that individuals may choose to diverge from choices of their friends, but the mechanisms in the two papers are fundamentally different. They attribute behavioral divergence to the possibility for group members to exchange information on risky alternatives (dishes, beers and wines) that have highly uncertain quality, while we control for learning by using standard choices and attribute divergence to people’s simple and yet powerful need to be different.

On the theory front, impressive attempts have been made by economists to analytically model the key tradeoffs associated with identity, norms and conformity. Bernheim (1994), for example, analyzes a model of social interaction in which individuals care about status (public perceptions about their predispositions) as well as intrinsic utility. He finds that norms can often be endogenous outcomes of individuals’ maximization of total utility, and they can be either persistent or transitory. He also finds an explanation for the development of subcultures with their own distinct norms. Our model is similar to his in that we also assume that an individual’s utility is the sum of his intrinsic utility and image-based utility (see empirical evidence in Toubia and Stephen (2013) in the context of Twitter). Our model differs from his, however, in that we do not treat status as a single variable that is positively correlated with one’s proximity to an ideal position in the network. Instead, we allow the image-based utility to increase with both being similar to others, and being different. The ability to (partially) separate these two components of image-based utility comes from the variation of adoption rate, which is positively associated with the two components with different intensities. Akerlof and Kranton (2000) investigate the role of identity in a variety
of economic issues and formulate a game-theoretic model in which two players with inherently different tastes move sequentially and the second mover’s divergence from the first mover’s choice can jeopardize both players’ identities. In case of divergence, the first mover may choose to “respond” which restores his own utility at a positive cost and causes a substantial loss to the second mover. Again, we hold a more favorable view toward divergence, and do not “punish” the individual in our model for being different.

The remainder of the paper is organized as follows. We introduce an analytical model of the tradeoff between the need to belong and the need to be different in the next section. In Section 3 we offer corresponding empirical evidence from a large scale field experiment in China and in Section 4 we discuss replication of these results in the United States. We offer managerial implications in Section 5 and conclude in Section 6.

2 A Model of the Needs to Belong and to Be Different

In this section, we provide a simple model to highlight the tradeoff in people’s balancing of their needs to belong and to be different. As summarized in Akerlof and Kranton (2000), there are many different ways to model these needs. To best align the model to our experiment, we take a minimalist approach and position the model in the context of a social networking platform. This approach enables us to keep the model straightforward and yet yielding rich implications for social media marketing campaigns.

Suppose that a user on a social networking platform who has an innate preference for a particular taste-driven choice, such as color, derives utility $b + u$ from his favorite option and $b$ from other options. $b > 0$ here is the baseline utility for having an option and $u \geq 0$ is the additional utility he gains from choosing an option that matches best with his taste.

Motivated by the numerous situations in which marketers go after new users or competitors’ customers by showing them adoption information, and also to remain consistent with existing findings that decision making in a group context often involves personal consumption dissatisfaction (Ariely and Levav 2000), we focus on scenarios in which individuals’ favorite options are different from the most popular choices among their friends.

When informed of the popular choice, user $i$ has three potential reactions. First, he may choose to ignore the message and do nothing. In this case his utility is $B + u + d(p)$, where $p \in [0, 1]$ is the adoption rate of the most popular choice among his friends, and $d(p) > 0$ is the participant’s utility being different from his friends. We assume $d'(p) > 0$, so that users derive more utility from being distinctive when their choice differs from a larger proportion
of their friends. Second, he may converge to what he has been told is the most popular choice. His utility is $B + s(p) - c_i$ in this case, where $s(p) > 0$ is his utility from conforming to his friends, and $c_i > 0$ is his cost, in terms of time and effort, to modify his choice. We assume $s'(p) > 0$ to capture the intuition that users derive more utility from conformity when their choice coincides with a larger proportion of their friends. Third, there is a theoretical possibility that the user would switch to a new option that is different from the most popular choice among his friends. His utility in this case is $b + d(p) - c_i$. Given that $u, c_i > 0$ for all $i$, this possibility is strictly dominated by the first reaction above (i.e., do nothing). Indeed, in our empirical studies later on, very few people take this action.

Comparing the first two reactions above, user $i$ chooses to conform to the popular color iff

$$c_i < s(p) - d(p) - u.$$ 

One can see from this condition that a participant is more likely to choose divergence when his cost of switching is high, his utility from conformity is low, and his utility from being different is high. Suppose that $c_i$ is i.i.d. with cumulative distribution of $F$ for all $i$. For a given adoption rate $p$, the probability of convergence is then $F(s(p) - d(p))$. Depending on the shapes of $s(p)$ and $d(p)$, this probability can either increase or decrease with $p$, as reflected in the two opposing hypotheses below.

**H1a:** As the adoption rate of the most popular color increases, participants are less likely to converge to that color.

If this hypothesis is supported, it suggests that $d'(p) > s'(p)$. That is, as the adoption rate increases, a user’s utility from being different grows faster than his utility from conformity. In other words, a high adoption rate is more likely to trigger divergence. The alternative hypothesis is:

**H1b:** As the adoption rate of the most popular color increases, participants are more likely to converge to the color.

If this hypothesis is supported, it suggests that $d'(p) < s'(p)$: a user’s utility from conformity outgrows his need to be different as the adoption rate increases. In this case, a high adoption rate is more likely to trigger conformity.

Suppose now that rather than learning about the most popular color among their friends, participants may instead learn about the most popular color among all users on the platform. By conforming to (diverging from) the popular choice, a user still derives utility from fitting
in (being different), but the adoption rate matters much less since a user typically does not interact with non-friends on the platform and does not directly observe their choices. Motivated by this situation, we assume that the utility from convergence (resp., divergence) becomes $S$ (resp., $D$). As a result, the user would choose to conform iff $c_i < S - D - u$, which leads to our next hypothesis.

**H2:** When informed of the most popular choice among all the platform’s users, the likelihood that a user will converge to that choice does not change significantly with its adoption rate.

Finally, to differentiate a user’s need to be different from his need to show such differences, we introduce a multiplier $m$ to his utility of being different. Suppose that, when a user perceives his distinctiveness from his friends to be more salient, his utility from being different becomes $m \cdot d(p)$. If $m > 1$, a user not only enjoys being different but also enjoys showing his distinctiveness. When $m < 1$, the user still enjoys being different, but prefers to hide such distinctiveness. With the salience multiplier, user $i$ would converge to the most popular color with a probability of $F(s(p) - m \cdot d(p))$. We hypothesize that this probability compares to the baseline divergence probability in the following fashion.

**H3:** When the adoption is low (high), the probability of convergence is lower (higher) as the user’s distinctiveness becomes more salient to his friends.

Intuitively, this hypothesis suggests that while users may enjoy being a minority and showing their distinctiveness to their friends, they may still not want to be seen as the only person to adopt a certain option. In other words, they will prefer to hide their unique choice when an overwhelmingly large number of friends choose another option. If this hypothesis is supported, it suggests that $m$ may be a function of the adoption rate and $m(p)$ is a monotonic function that decreases in $p$.

### 3 Field Experiment on Kaixin

In this section, we test the four hypotheses above by conducting a large-scale field experiment on Kaixin, a leading social networking platform in China.
3.1 Background of Kaixin

Founded in March 2008, Kaixin has more than 161 million registered users as of June 2014, roughly ten percent of the Chinese population. In 2010, Kaixin ranks as the 13th most popular website in China and 67th in the world according to Alexa. According to Wikipedia, Kaixin’s success can be partly credited to Internet censorship in the People’s Republic of China. Due to the permanent blockage of foreign social-networking websites such as MySpace, Facebook, Twitter and YouTube since the summer of 2009 following the Ürümqi riots, many Chinese nationals turned to domestic sites, leading to a spike in Kaixin’s membership.

Unsurprisingly, a significant 89.2% of the site visitors are based in China. According to a 2009 national study from the Chinese Internet Network Information Center (CNNIC), Kaixin is one of the most popular social networking sites (SNSs) in China, hosting 26.4% of all SNS users in China. Compared to other Chinese networking sites, Kaixin has superior coverage of urban Internet users and appeals more to white-collar office workers who love surfing the site at work. A typical user of Kaixin, for example, is 25-34 years old and has a college degree. Kaixin users are highly active. In 2010, it averages 34 page views and 33 minutes spent on the site per user, numbers that are about twice as high as the competition. Similar to Facebook, the majority of users on Kaixin are registered with their real names and two users have to mutually agree to a friendship before they can access each other’s information as friends.

3.2 Experimental Design

We conduct the experiment in the context of a popular and free game on Kaixin, “Virtual Homes.” This game is one of the more than 200 applications on Kaixin and is built into the site so that all registered users have automatic access to the game. It is a non-competitive game for users to customize the looks of a virtual house.

When playing the game, users can choose the color of the walls inside their virtual houses. Six colors are available: yellow, green, pink, blue, red, and gray. Figure 1 provides an illustration of the game (translated from Chinese).

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12 All data in this paragraph are taken from http://www.alexa.com/siteinfo/kaixin001.com (accessed on May 2014) unless otherwise mentioned.
14 Other popular Chinese social networking sites are QQ XiaoYou, XiaoNei/Ren Ren, Sina Space, and 51.com.
15 http://venturebeat.com/2010/04/07/china’s-top-4-social-networks-renren-kaixin001-
Figure 1: Screen Shot of the “Virtual Homes” Application

We pick a random sample out of active users of this application in January to March 2011 who have more than ten friends as subjects of our experiment.\textsuperscript{15} We impose this requirement of number of friends to ensure the credibility of our experimental message because it might be easy for users with only a few friends to remember their friends’ color choices. Subjects are not aware of the experiment and each user could participate only once in our experiment.

On average, a subject in our experiment has 69 friends. Prior to the experiment, when a subject picks a color and confirms his choice by clicking the “Save” button, Kaixin records his color choice, applies it to her virtual house, and displays “Successfully Saved!” in a pop-up window.

During the experiment, we assign each subject to one of three experimental conditions (A, B, or C) with equal probability. The conditions differ by the experimental message that we insert into the pop-up window mentioned above. In condition A, a user is shown an experimental message that shows the (randomly generated) most popular color supposedly chosen by his friends and the (randomly generated) adoption rate of that color. To be consistent with our model, the popular color is different from the subject’s original choice: we simply assign equal probability (20\%) to the other five colors when generating the most popular color.

\textsuperscript{15}Our experiment runs from January to March 2011 in two phases for a total of three weeks. After the first phase in January 2011, we check the data to ensure that all procedures in the experiment are implemented correctly. We then re-launch the experiment in March 2011 for a second phase.
popular color.

In condition B, we display the same message as in condition A but add the following sentence: “Don’t forget to show your newly painted house to your friends,” which is henceforth referred to as the social message. As an example of the experimental messages, Figure 2 shows a pop-up window that a subject could see in this condition (translated from Chinese).

Figure 2: Screen Shot of the Message Window for a Random Subject in Condition B

In condition C, we inform the subject of the (randomly generated) most popular color supposedly chosen by all users on Kaixin and randomly generated adoption rate of that color. The popular color here can be any one of the six available colors with equal probability. Figure 3 presents a flowchart of the experimental design.

We record the subjects’ choices of wall colors before and after they see the experimental messages. The before choice is recorded as CurrentColor. The randomly generated most popular color among a subject’s friends (all Kaixin users) is recorded as FriendColor (GlobalColor). For all the subjects, the pop-up window offers two buttons, “Repaint” and “OK.” We record the subject’s final choice of wall color as FinalColor. The circles in Figure 4 illustrate the points in time at which messages are generated and colors recorded.

We take several measures to ensure that our messages could not be easily detected by the subjects as being randomly generated. First, as mentioned, we restrict our subjects to be users with more than ten friends to avoid users who might remember all their friends’ color choices and thus question the validity of our message. By the time when we show
Figure 3: Design of the Experiment

Subject paints wall

Subject already in the experiment?
- Yes: Exclude subject from experiment
- No

Subject has more than 10 friends?
- Yes: Show information on **GlobalColor**
- No

Show information on **GlobalColor**
Generate a random color that is different from **CurrentColor**. Randomly generate an adoption rate.

Subject enters experiment

Show information on **FriendColor**
Generate a random color that is different from **CurrentColor**. Randomly generate an adoption rate based on the number of the subject’s friends.

Show message: “Don’t forget to show your newly painted house to your friends!”

Record subject’s action

Show social message?

1/3 Condition C
2/3 Conditions A and B
½ Yes Condition B
½ No Condition A
the pop-up window, the subjects can no longer visit their friends’ houses to verify the color choices. Second, to make the adoption rate of friends’ popular color look more plausible, we use the following procedure. For a subject with \( n \) friends (\( n > 10 \)), suppose \( x \) is the smallest integer such that \( x/n > 1/6 \). We first generate a random integer \( m \) between \( x \) and \( n \), and then use \( [m/n] \) as the adoption rate. Hence, a subject with twenty friends would only be given adoption rates 20\%, 25\%, 30\%, and so on. This procedure is designed to make it hard for subjects to question the experimental message based on the number of friends they have on the site. Third, in all the experimental messages, we use a vague word, “Recently,” before giving information about the most popular color choice (see Figure 2), so that users are unsure over what time period this supposed popular color is generated and thus, again, less likely to question its validity. Finally, we conduct robust checks to our empirical analysis in which we exclude adoption rates that are higher than certain thresholds as these rates might be harder to believe, and show that our results continue to hold.

Our experimental design has three distinct features. First, by randomly generating the most popular colors, we minimize the influence of the correlation between a subjects’ color preferences and those of their friends. Second, a subject’s choice of wall color is observed only by her friends and not by other users on the site. Therefore, our subjects do not have the pressure to signal group identities to the general public by conforming to their friends’ choices. Third, learning is unlikely to drive subjects’ behavior in our setting, as all the six colors are standard and the subjects could experiment with them before confirming their
choices.

3.3 Analysis

Although we believe that our experimental design minimizes the usual confounding factors, we could have introduced prominence and warning effects by displaying the experimental messages. That is, subjects could be more likely to either switch to or avoid a particular color after seeing it being mentioned in our message, simply because it makes that color more prominent to them. Subjects could also have interpreted the messages as warnings and changed their color choices to avoid seeing the same messages again.

To control for these effects, we focus our analysis on how subjects’ behavior changes according to the adoption rate of the most popular color. As long as the prominence and warning effects remain largely unchanged as we vary the adoption rate, the changes in the subjects’ behavior could be attributed to the variation in their needs to belong and to be different.

3.3.1 Data

While the initial range of adoption rates of most popular colors is \([\frac{1}{6}, 1]\), our initial analysis suggests that the adoption rate does not seem to affect subjects’ behavior when it is below 50%. This result is consistent with the intuition that a choice typically has to be adopted by the majority of a group in order for normative social influence to be effective, and that a user is more likely to be seen as different when his choice differs from that of the majority of his friends. Given this result, in what follows, we focus our attention on subjects who are shown adoption rates that are larger than 50%.

In total, we have 16,298 subjects in the final data set, with 5,440 in condition A, 5,423 in condition B, and 5,435 in condition C.\(^{17}\) Table 1 presents summary statistics for all the variables used in our analysis. The variable Converge is 1 if a subject decides to adopt the same color as the most popular color indicated in the experimental message.

The adoption rate, \(\% \text{ with Popular Color}\), ranges from 0.5 to 1 with a mean of 0.73 across all subjects in our final data set. The dummy variable Friend Info indicates whether the subject receives information about the most popular color used by his friends or by Kaixin.

\(^{16}\) We think this is a reasonable assumption and find preliminary evidence for it: the subjects’ behavior does not change with the adoption rate in condition C where information on the most popular color among all Kaixin users is shown. We discuss this assumption further in Section 3.3.2.

\(^{17}\) Subjects are assigned into these conditions by a random number generator on the site. As a result, the numbers of users are not exactly the same across the three conditions.
users. The dummy variable \textit{Include Social Msg} indicates whether a social message is sent to that subject, with a mean of 0.33 by design.

Table 1: Summary Statistics for Subjects in Our Experiment

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Converge</td>
<td>16,298</td>
<td>0.04</td>
<td>0.20</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>% with Popular Color</td>
<td>16,298</td>
<td>0.73</td>
<td>0.16</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>Friend Info</td>
<td>16,298</td>
<td>0.67</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Include Social Msg</td>
<td>16,298</td>
<td>0.33</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age</td>
<td>16,298</td>
<td>32.06</td>
<td>7.80</td>
<td>18</td>
<td>60</td>
</tr>
<tr>
<td>Female</td>
<td>16,298</td>
<td>0.69</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total Number of Friends</td>
<td>16,298</td>
<td>68.67</td>
<td>96.28</td>
<td>11</td>
<td>1,024</td>
</tr>
<tr>
<td>GDP Per Capita (RMB)</td>
<td>14,257</td>
<td>42,245.82</td>
<td>15,132.27</td>
<td>7,074</td>
<td>71,808</td>
</tr>
<tr>
<td>Outside China</td>
<td>16,298</td>
<td>0.02</td>
<td>0.14</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

As the subjects’ behavior could also vary depending on demographic characteristics, we construct several demographic variables based on information that is self-reported by the users when they register with Kaixin. The variables \textit{Age} and \textit{Female} record the age and gender of each subject. The average age of the subjects is about 32. Consistent with prior studies of social-network users, females are more represented than males in this application, with the mean of the dummy variable \textit{Female} being 0.69.\textsuperscript{18} \textit{Total Number of Friends} records the total number of friends each subject has upon entering our experiment. There is substantial variation in the subjects’ total number of friends, ranging from 11 to the maximum number allowed by the site, 1,024, with a mean of 68.67.

We also collect information on the subject’s hometown, which is also self-reported but not mandatory. About 87.5\% of all subjects in our dataset report this information. For each hometown, we obtain data on its GDP per capita (\textit{GDP Per Capita}) from the 2007 China Statistical Yearbook published by the National Bureau of Statistics of China to gauge its relative affluence level.\textsuperscript{19} The mean of \textit{GDP per capita} is RMB 42,246 and it varies from RMB 7,074 to RMB 71,808. Finally, we obtain information on whether the subject currently

\textsuperscript{18}See \url{http://blog.nielsen.com/nielsenwire/social} for 2012 Nielson report on social media, accessed in April 2012. See also \url{http://en.wikipedia.org/wiki/Gender_differences_in_social_network_service_use} for a discussion on gender differences in SNS usage.

\textsuperscript{19}The ranks of cities in China based on their GDP per capita remain mostly unchanged over time. As a robustness check, we use the ranks of the cities instead of their actual levels of GDP per capita and obtain similar results.
lives in China or outside China, which is required and self reported by the subjects when they register with Kaixin. The dummy variable, *Outside China*, take the value of 1 if the subject lives outside China at the time of registration and 0 otherwise. This variable has a mean of 0.02, suggesting that only 2% of users in our data live outside of China at the time of our experiment.  

### 3.3.2 Model-Free Evidence

Figure 5 presents model-free evidence on how the probability of convergence, defined as a subject’s choosing the most popular color as indicated in the experimental message, varies with the adoption rate of that color. On average, the probability of convergence is low, ranging between 3% and 6%: subjects are reluctant to repaint their walls once they make the initial color choices.

![Figure 5: Probability of Convergence in conditions A and C](image)

The solid black line in Figure 5 demonstrates that, in condition A, the average likelihood of a subject’s converging to the most popular color among her friends *decreases* with the adoption rate of that color. The average probability of convergence drops 54.9% when the adoption rate increases from \((50, 60]\) to \((90, 100]\), suggesting that the greater popularity of 

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20This number is much lower than the percentage of overseas users on Kaixin, suggesting that overseas users are less active in this game than domestic users.

18
the majority choice *de-motivates*, rather than motivates, our subjects to conform. This pattern is consistent with H1a, suggesting that while normative social influence grows with the adoption rate, the need for uniqueness may be growing even faster.

To rule out the possibility that the observed downward trend is a result of the variation in prominence or warning effects, we conduct the same trend analysis for condition C, as demonstrated by the dashed red line in Figure 5, which is mostly flat ($p = 0.240$). This confirms H2 and our intuition that subjects do not care much about the choices of non-friend users as only friends could see their color choices. The contrast between the two curves hence provides further support that the changes in our subjects’ behavior in condition A are due to reactions to the choices of their friends.

Figure 6 contrasts condition A (popular color among friends) with condition B (information in condition A and the social message). The blue dashed line (condition B) is below the solid black curve (condition A) as long as the adoption rate is not extremely high ($p = 0.043$). This result is consistent with H3, suggesting that subjects’ desired saliency of their distinctiveness changes with the adoption rate of the majority choice. In particular, when the adoption is high but not near unanimity, subjects enjoy being seen as distinctive, but when the majority choice becomes adopted almost unanimously, subjects tend to be keener to conform to this strong norm in order to avoid being seen as ‘strange outliers’ in their friend circles. A back-of-the-envelope calculation indicates that, when the adoption rate exceeds 88%, subjects are more likely to converge to the popular color after seeing the social message.

![Figure 6: Probability of Convergence in Conditions A and B](image-url)
3.3.3 Regression Results

We now turn to regression analysis to verify that the patterns that we observe in the figures above are statistically significant.

The dependent variable in our regression is Converge, and we use linear probability models to ease the interpretation of interaction variables. In our analysis, 100% of the predicted probabilities lie between zero and one. As shown in Angrist and Pischke (2008) and Horrace and Oaxaca (2006), linear probability models with robustness standard errors yield unbiased and consistent estimates, and our results remain robust when we use limited dependent variable models. We report the main results of our regression analysis in Table 2.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Condition A</th>
<th>Condition C</th>
<th>Conditions A and C</th>
<th>Conditions A and B</th>
</tr>
</thead>
<tbody>
<tr>
<td>% with Popular Color</td>
<td>-0.047**</td>
<td>0.010**</td>
<td>-0.010</td>
<td>-0.021*</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% with Popular Color × Friend Info</td>
<td>-0.057**</td>
<td>-0.042**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.019)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Include Social Msg</td>
<td>-0.008*</td>
<td>-0.046**</td>
<td>-0.047*</td>
<td>-0.046**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.019)</td>
<td>(0.020)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.000</td>
<td>-0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>-0.008*</td>
<td>-0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Number of Friends</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(GDP Per Capita)</td>
<td>-0.011**</td>
<td>-0.011**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outside China</td>
<td>-0.023**</td>
<td>-0.011**</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Heteroskedasticity-adjusted standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. 

Table 2: Regression Results on the Linear Probability to Converge
In Model (1), we restrict the analysis to subjects who receive information on FriendColor without the social message (condition A). We find that a subject’s probability of convergence to FriendColor decreases with the adoption rate of that color among her friends, confirming H1a (and hence invalidating H1b). In Model (2), we repeat the same analysis with subjects who receive information on GlobalColor (condition C) and find that the adoption rate has no significant effect on the probability of them converging to that color, confirming H2. In Model (3), we include observations in both conditions A and C, use the dummy FriendInfo to control for differences in convergence probabilities between the two conditions, and interact the dummy with % with PopularColor to capture the difference in the slopes. The interaction is significant, suggesting that subjects thoughtfully react to the information in the experimental messages and care more about the adoption rate of FriendColor.

In Models (4)-(6), we include subjects who receive information on FriendColor (condition A) and those who receive information on FriendColor along with the social message (condition B). We include the dummy variable, Include Social Msg, in Model (4) to indicate whether the subject receives the social message, and its interaction with % with PopularColor in Model (5). The results confirm prior evidence that when the adoption rate of FriendColor is below (above) 88%, subjects are less (more) likely to converge after seeing the social message.

After controlling for demographics, we obtain similar results in Models (6) and (7): a subject is less likely to choose the color that is most popular among his friends as the adoption of that color increases, except when the adoption rate exceeds 92% and the social message is displayed. These findings provide further support for H3.

With regard to the demographic variables, age is not significant in predicting a user’s likelihood to converge, but it appears that female subjects have a stronger need to be different: their probability of convergence is lower than that for male subjects by 0.8 percentage points. Subjects born in more affluent hometowns, measured by GDP per capita, are less likely to converge, and those who live outside China are less likely to converge. As Kaixin uses a text box for users to report their hometown information, it is hard to tabulate the locations as some users prefer to be vague (reporting only the state or country) while others prefer to be specific (reporting the city). Nonetheless, our readings of the data suggest that most of these users live in a western culture such as Australia, Canada or the U.S.
3.3.4 Robustness Checks

We conduct two robustness checks to rule out alternative explanations. First, we are concerned whether users of a particular current color behave systematically differently from users of another color, and if so, whether such color preferences might drive our results. As a robustness check, we add dummies to indicate users’ current colors as additional control variables. The results show that these dummies are insignificant and our main results continue to hold.

Second, we are concerned that our results might be driven by the creditability of our randomly-generated messages. As the percentages we use in these messages increase, it is possible that users are less likely to believe our messages and thus are less likely to take actions. While this possibility does not explain the upward tale in condition B (with the social message), we conduct a robustness check by restricting the percentages in our message to be between 50% and 70%. If users are more likely to be influenced when the percentages are small and divergence is entirely driven by the creditability of our messages, we should not observe significant divergence for this subset of the data. Repeating the analysis, we continue to find significant evidence for divergence.

4 Replicating the Study on Amazon Mechanical Turk

To examine whether our results could be generalized to a non-Asian population, we replicate the study on Amazon Mechanical Turk (henceforce MTurk). From December 4 to 6, 2013 and from February 19 to 20, 2014, we recruit 934 subjects who live in the U.S. from MTurk and direct them to a Qualtrics survey in which we replicate the Kaixin experiment by asking them to imagine painting a virtual house on Facebook.

We use the same experimental design for the MTurk study and randomly assign the subjects to one of the same three conditions. After completing initial screening questions, a subject is asked to pick a wall color for his virtual house. To be consistent with our Kaixin experiment, the color choices in this question are screen shots taken directly from Kaixin. The order of the colors is randomized across participants to avoid potential sequencing effects. On the next question, the subject is asked to confirm his color selection with all the colors presented in a different order. In an effort for control for data quality, we eliminate responses in which answers to these two questions are inconsistent. Next, we show experimental messages to the subject and give them an option to repaint the house. We then record the

21For example, one question ensures that they have a Facebook account.
randomly generated *FriendColor* and the subject’s choice of the *FinalColor*. As Qualtrics enables us to ask open-ended questions, we ask a follow up question on why the subject chooses (or not) to change his color choice. We finish the survey with demographic questions.

Figure 7 shows how the probability of convergence changes with the adoption rate of the (randomly generated) most popular color among the subject’s Facebook friends. Due to differences between the two platforms we cannot directly compare the probabilities of convergence, but we are able to obtain additional results to support the hypotheses. The patterns of the lines in Figure 7 are similar to those in Figure 5 from the Kaixin experiment, confirming the earlier results on H1a and H2.\(^{22}\) Answers to our open-ended question turn out to be quite helpful in confirming our subjects’ motivations for their choices. Many participants refer directly to their need for uniqueness (e.g., “I like to be different,” “I figure the most opposite color of green would be orange”) or their need to fit in with their friends’ choices (e.g., “I didn’t want to see my red house next to a bunch of pink houses,” “Following the trend,” “Because I’m a conformist and I don’t want to stand out and look weird”).

Figure 7: Probability of Convergence in conditions A and C on MTurk

Consistent with our Kaixin results and H3, Figure 8 shows the comparison of conditions A and B and confirms that the social message appears to markedly increase (decrease) the convergence of subjects’ choices when adoption is nearly (not nearly) unanimous.

We use regressions again to confirm the observed patterns. Table 3 reports regression results for the MTurk study that confirm our observations from the figures. Because of the

\(^{22}\)Although the convergence for condition C now looks considerably less flat than in Figure 5, a linear regression confirms that the slope is not significantly different from zero.
survey design, our control variables are somewhat different from those in the field experiment. For example, instead of the exact age of each subject, we obtain data on their age ranges. Instead of inferring income levels of subjects based on their locations, we now obtain direct data on their income ranges. We also obtain data on education background and marriage status. Similar to what we find in the Kaixin experiment, female subjects are less likely to conform. Subjects with higher income are also less likely to conform. Interestingly, widowed subjects are less likely to conform than single or married subjects while divorced subjects are more likely to conform.

Putting the Kaixin and MTurk studies together, our results suggest that people have a much stronger need to be different than to be the same, especially in the realm of online social networks.
Table 3: Regression Results on the Linear Probability to Converge

<table>
<thead>
<tr>
<th></th>
<th>Condition A</th>
<th>Condition C</th>
<th>Conditions A and C</th>
<th>Conditions A and B</th>
<th>Conditions A and B</th>
<th>Conditions A and C</th>
</tr>
</thead>
<tbody>
<tr>
<td>% with Popular Color</td>
<td>−0.249</td>
<td>−0.238</td>
<td>0.145</td>
<td>0.145</td>
<td>−0.238</td>
<td>0.145</td>
</tr>
<tr>
<td>× Friend Info</td>
<td>−0.394</td>
<td>0.299</td>
<td>(0.213)</td>
<td>(0.170)</td>
<td>0.030</td>
<td>−0.355</td>
</tr>
<tr>
<td>Include Social Msg</td>
<td>0.030</td>
<td>−0.355</td>
<td>(0.032)</td>
<td>(0.164)</td>
<td>−0.321</td>
<td>0.106</td>
</tr>
<tr>
<td>% with Popular Color</td>
<td>−0.106</td>
<td>−0.249</td>
<td>(0.048)</td>
<td>(0.059)</td>
<td>−0.118</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Age ≥ 20 &amp; Age &lt; 30</td>
<td>0.106</td>
<td>0.299</td>
<td>(0.084)</td>
<td>(0.088)</td>
<td>0.118</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Age ≥ 30 &amp; Age &lt; 40</td>
<td>0.097</td>
<td>0.145</td>
<td>(0.099)</td>
<td>(0.100)</td>
<td>0.118</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Age ≥ 50</td>
<td>0.006</td>
<td>0.145</td>
<td>(0.100)</td>
<td>(0.100)</td>
<td>0.118</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Female</td>
<td>−0.057</td>
<td>−0.094</td>
<td>(0.034)</td>
<td>(0.048)</td>
<td>−0.049</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Income ≥ $20K &amp; Income &lt; $30K</td>
<td>−0.094</td>
<td>−0.049</td>
<td>(0.048)</td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income ≥ $30K &amp; Income &lt; $40K</td>
<td>−0.253</td>
<td>−0.150</td>
<td>(0.203)</td>
<td>(0.207)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income ≥ $40K &amp; Income &lt; $50K</td>
<td>−0.277</td>
<td>−0.314</td>
<td>(0.203)</td>
<td>(0.207)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income ≥ $50K</td>
<td>−0.062</td>
<td>−0.049</td>
<td>(0.046)</td>
<td>(0.056)</td>
<td>−0.049</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Education=high school</td>
<td>−0.253</td>
<td>−0.314</td>
<td>(0.203)</td>
<td>(0.207)</td>
<td>−0.049</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Education=college</td>
<td>−0.277</td>
<td>−0.314</td>
<td>(0.203)</td>
<td>(0.207)</td>
<td>−0.049</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Education=graduate or professional school</td>
<td>−0.062</td>
<td>−0.049</td>
<td>(0.046)</td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marriage=married</td>
<td>0.051</td>
<td>0.051</td>
<td>(0.039)</td>
<td>(0.039)</td>
<td>0.051</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Marriage=separated</td>
<td>0.030</td>
<td>−0.125</td>
<td>(0.254)</td>
<td>(0.060)</td>
<td>0.051</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Marriage=divorced</td>
<td>0.030</td>
<td>−0.125</td>
<td>(0.254)</td>
<td>(0.060)</td>
<td>0.051</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Marriage=widowed</td>
<td>0.030</td>
<td>−0.125</td>
<td>(0.254)</td>
<td>(0.060)</td>
<td>0.051</td>
<td>(0.039)</td>
</tr>
</tbody>
</table>

Number of Subjects: 336 253 589 681 681 664
R-Squared: 0.010 0.003 0.007 0.001 0.010 0.036

Note: Age < 20, Income < $20K, Education = less than high school, and Marriage = single are used as benchmark groups. Heteroskedasticity-adjusted standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.
Marketing based on social connections through social networks is an attractive proposition to firms. Such social advertising should be superior to traditional advertising because consumers tend to trust their friends’ opinions more.

This promise of social networks’ value, however, depends on a very crucial assumption: After observing his online friends’ adoption behavior, a user would like to converge and follow with the same behavior. An extensive and growing literature documenting various influences of social connections seems to imply that publicizing one’s friends adoption behavior should trigger his or her similar actions. Our field experiments show that this belief may not always be true. We argue that it is important to consider contextual factors when examining how users on social networking platforms trade off their psychological needs to belong and to be different. Such contextual factors can be related to users’ preexisting preferences, their need to signal social identity to “out-group” individuals, and their resolving uncertainty in product quality through observational learning. While previous research has concluded that all these factors trigger users’ need to be similar to their friends and lead to behavior convergence, this study examines the arguably more fundamental need to be different.

We show that once the contextual factors are removed, the need to be different leads to behavior divergence. In this situation, making friends’ majority choice salient leads to the deviation from this majority choice. This finding may help explain why some social media advertising efforts are successful while some others fail. According to a recent survey conducted by the Public Relations Society of America, 40% of the respondents describe social media advertising returns as either “nothing to write home about” or “leaving a lot to be desired.” Without examining the importance of contextual factors, even the same campaign may result in different outcomes.

For marketers, this study suggests that merely finding the influential “opinion leaders” in social networks is not enough. If the contextual factors are relatively weak, users’ innate need to be different may become dominant and the behavior divergence may drive social advertising campaigns to failure.

In real-life situations, one or more of the contextual factors may coexist with the fundamental need to be different. It is therefore very important to examine the relative importance of these factors before conducting social advertising. For example, if social identity is important to the users, then showing friends’ adoption choice is likely to exert the pressure

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23http://www.prnewsonline.com/topics/social-media/2014/05/05/when-it-comes-spending-on-social-facebook-dominates/
for them to follow. If uncertainty in product quality dominates, showing majority (not necessarily friends’) choice may be the most effective. If, however, users’ need to be different dominates, social advertising that highlights majority choice should be cautioned.

Our results offer some additional insights regarding to when to avoid social advertising. For example, we find that people born from more affluent towns and females are more likely to be diverging from majority choice. An advertiser with such audiences should be careful when implementing social advertising campaigns because in these situations behavior divergence is more likely triggered. Even if social advertising works due to dominance of external factors, an advertiser should not alert the users that their friends may observe their actions. In this case, friends’ adoption information becomes a double-edged sword: On the one hand, social advertising relies on it to work, but on the other hand, it increases the chance for social advertising to fail. Finally, at least in our context, unanimous adoption is a strong pressure for subjects to converge to majority choice when reminded that their choice can be seen by friends. If some behavior is adopted unanimously, social advertising with such a reminder is likely to be successful.

6 Concluding Remarks

In this paper, we study the tradeoff between people’s needs to belong and to be different by first formulating a theoretical model and then testing our predictions about these two motivations. We find that users of social networking sites have a dominating need to be different from their friends, and this need grows more strongly than their need to fit in by conforming to the most popular choice among their friends as the adoption rate of that choice increases. We also find that pushing for conformity by reminding users of the visibility of their choices to their friends may in fact increase their desire to be different, unless the adoption of the most popular colors is near unanimity.

While our results demonstrate that people have innate needs to be different, they stand in sharp contrast with popular wisdom and existing studies on herding. We attribute this contrast to the fact that, due to its design, the role of observational learning, pre-existing taste similarities, and identity signalling is minimized in our study, which enables us to focus on how people trade off their needs to belong and to be different.

It is important to acknowledge boundaries of our study. In particular, we focus on taste-driven choices among alternatives that are horizontally differentiated, in a context where uncertainty along vertical dimensions (e.g., quality) is minimized. While we do this
on purpose in the current study to highlight the tradeoff of the two fundamental human needs, we expect conformity to be stronger in contexts where the alternatives could lead to uncertain outcomes. Even when their choices are driven mostly by individual tastes, people may still be able to find subtler ways to satisfy their needs to be different. Future research, for example, could explore when and whether people might choose to customize a popular choice to their own tastes, or to adopt a different choice altogether. Finally, we also expect conformity to be stronger in exclusive social groups that are sensitive about or proud of their identities.

References


