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Social-Media, Influencers, and Adoption of an Eco-Friendly Product: Field Experiment Evidence from Rural China

Abstract

Can low-cost marketing tools that are used to enhance business performance also contribute to creating a better world? The authors investigate the role of online social media tools in alleviating customer (farmer) uncertainty and promoting the adoption of a new eco-friendly pesticide in rural China. The key finding is that even for a new product such as a pesticide, a low-cost social media support platform effectively promotes its adoption. The combination of information from peers and the firm on the platform facilitates learning about product features and alleviates uncertainty associated with product quality and appropriate product usage. Nevertheless, at the trial stage of the funnel the platform underperforms the firm's customized one-on-one support because available information does not resolve uncertainty in supplier credibility and product authenticity. Having an influencer on the platform, albeit not an expert on this product, vouching for its credibility helps resolve this funnel-holdup problem. From a theoretical perspective this paper provides suggestive evidence for referent influence and credibility signaling on social media platforms and their consequences for new product trial. The authors also provide direct empirical evidence on how information facilitates learning; a phenomenon typically assumed as being present in marketing studies estimating learning models.

Keywords: social media, mobile marketing, emerging markets, field experiment, innovation adoption

Statement of Intended Contribution

This paper addresses the question: can low-cost marketing tools that are typically used to enhance business performance also create a better world? The use of toxic pesticides has been viewed as a global problem. In this paper, we examine the role of online social media tools in facilitating the adoption, by farmers, of an environmentally friendly new technology - a non-toxic pesticide - to combat this problem.

Our research contributes to the marketing discipline in the following ways. First, we show that low-cost marketing tools can indeed facilitate adoption but also have some limitations. While our primary focus is on social media tools, we empirically compare the causal effects of multiple approaches to influencing adoption behavior in a B2B environment. In this regard, previous literature has typically addressed one specific marketing tool and mostly in Business-to-Consumer (B2C) categories. Second, we examine multiple behavioral outcomes over the course of the adoption funnel and discuss the challenges associated with these outcomes and possible solutions. Third, we disentangle the effect of a new type of influencer, the "eminent village personality," from the effect of the social media platform by using a randomized controlled trial; we also provide suggestive evidence on the mechanism behind the influence. Finally, our research is about technology adoption in developing areas of the world, a topic that has not received much attention in the marketing literature.

Our research should be of interest to agents from firms, NGOs, and the government who seek to promote low-cost adoption of new products and technologies. What is the most effective medium for communicating the benefits and overcoming the barriers to their adoption? Are online social interactions a more credible source of information than firm-initiated interventions? Can influencers who do not have product related expertise foster trust and stimulate trial and adoption behavior in a mobile social media platform? Our research results should provide insights into the design of marketing campaigns and the selection of communication channels to promote the adoption of such products especially in developing markets.

In this study, we investigate how low-cost, online marketing tools can create a greener and healthier world by promoting the diffusion of a new pesticide technology in rural China. For decades, pesticides have been applied to protect crops and livestock from pest infestations, to increase crop yields, and to improve food production (Alexandratos and Bruinsma 2012). However, pesticides are a double-edged sword and have raised serious concerns about food safety, environmental protection, and sprayers' health (see a brief review of the harm of pesticides in Web Appendix W1). According to the U.S. Environmental Protection Agency (2018), 68 pesticides have been classified as potential carcinogens; and every year 200,000 people die because of toxic pesticides (Science and Technology News 2017). Therefore, promoting the use of safe and green new pesticide technologies is critically needed to preserve ecological security.

However, "getting a new idea adopted, even when it has obvious advantages, is difficult" (Rogers 2003, p.1). By implementing a field experiment in 34 villages and more than 700 farmers in rural China, our paper seeks to understand whether a potentially low-cost approach based on a widely available social media platform, can be used to alleviate a major deterrent that hinders the adoption of a new technology: customer uncertainty. Customers, especially those in emerging markets and in rural areas face several types of uncertainty. These include uncertainty regarding: (i) the authenticity of the new product and supplier credibility (Hada, Grewal, and Lilien 2014) given previous experiences with unscrupulous "fly-by-night" operators (for example, the fake seeds problem in China (Business News 2014) and India (Agriculture News 2017)); (ii) the "objective" quality of the product or the "match value" of the product to the potential user (e.g., Erdem and Keane 1996; Crawford and Shum 2005; Ching and Ishihara 2010); and (iii) how best to use or apply the technology in order to get the best outcomes from it (Hanna, Mullainathan, and Schwartzstein 2014; Evenson and Westphal 1995). The traditional marketing literature has focused on how uncertainty is resolved vis-à-vis (ii) since (i) is usually not a concern and (iii) is usually not an issue in most categories studied.[1] One unique feature of our paper is that the technology and context we consider involves all three types of uncertainty.

The previous literature has explored several approaches to providing information to prospective users in rural markets so as to resolve their uncertainties. These include self-experimentation and external information obtained either via social interaction with peers or information from firms or governmental organizations (Conley and Udry 2010).[2] Although recent literature has highlighted the role of online social media in consumer product adoption (e.g., Godes and Mayzlin 2004; Liu 2006; Trusov, Bucklin, and Pauwels 2009), its use as a support platform has not been explored in the literature in a Business-to-Business (B2B) setting in rural markets.[3] In such support platforms, consumers interact with each other online and these interactions are supplemented by "broadcast" information where the firm addresses issues raised by consumers on the platform.

In the context of online social media, the literature has studied the roles of influencers in consumer marketing (e.g., Goldenberg et al. 2009; Katona, Zubcsek, and Sarvary 2011; Gong et al. 2017) and opinion leaders in business marketing (Hada, Grewal, and Lilien 2014; Iyengar, Van den Bulte, and Valente 2011; Nair, Manchanda, and Bhatia 2010). A second unique feature of our study is that we measure the additional impact on adoption, if any, of complementing the social media platform with an influencer. Quantifying the impact of an influencer however, is not straightforward when the technology is new and so there are no "expert" users of the technology who can serve as opinion leaders or early adopters to promote the product. Instead, as influencers, we examine the role of "eminent village personalities," whose opinions are valued across a broad set of topics, even if they lack expertise specific to our product. This is another unique aspect of the paper. To evaluate the cost-benefit tradeoffs to using such platforms, we also compare the effects to (a) a more traditional firm initiated one-on-one support approach (Cohen, Agrawal, and Agrawal 2006); (b) when the consumer tries to resolve uncertainties via self-experimentation. Differences across these information sources have implications for managers looking to resolve uncertainties in the adoption of their new technologies.

The diffusion of pesticides involves both trial and ultimate adoption of the product. Further, the nature of uncertainties facing potential users can be different in different stages. For example,

while product authenticity and supplier credibility may be critical to get a user to try a product, ultimate adoption is unlikely unless the user can understand how best to use the product to obtain the greatest benefit from adopting it. A fourth distinguishing feature of our study is that we consider multiple behavioral outcomes along the adoption funnel: trial in the initial stages after introduction, cumulative trial behavior, and ultimate adoption.

We use a randomized control trial to measure the causal effects of marketing tools in changing behaviors (see Banerjee and Duflo 2011; De Janvry, Sadoulet, and Suri 2017, for a review). We launched a "one-thousand-farmers" program in three rural areas in two provinces in China, lasting sixteen months from April 2017 to August 2018. First, we spent time "in the field" to understand users' production processes with the new technology, the obstacles encountered, and how users make decisions given limited access to information and other constraints. With this knowledge, we designed a field experiment to quantify the effects of alternative information sources and marketing tools in the adoption process.

Our results reveal the following: (1) The social media platforms (both with and without an influencer) result in significantly higher adoption rates than the baseline self-experimentation condition. (2) However, when the platform is complemented by an influencer, adoption rates are significantly higher than when not using one. (3) The source of this difference lies in the differential trial rates across groups rather than in adoption rates conditional on trial. (4) The higher trial rates can be attributed to the influencer's early encouragement to try the product. (5) Traditional marketing with personalized one-on-one telephone support yields similar cumulative trial and adoption rates as the influencer complemented social media platform. (6) However, personalized telephone support has a 35% lower return on investment (ROI) due to its higher associated costs. Thus from a cost-benefit perspective the social-media support platform with influencer is able to deliver comparable performance at a lower cost in our context.

Looking at the volume and nature of posts on the social media platforms, the differential impact of the influencer in the early trial period is consistent with trust building to eliminate uncertainty regarding the product and supplier (Kraft-Todd et al. 2018; French, Raven, and

Cartwright 1959), rather than social learning about product features from non-influencers. Further, by directly measuring the extent of learning about the various product features by those who tried the product across both social media conditions, we find comparable learning outcomes across the two conditions. Nevertheless, there are certain features of the product for which learning falls short of that under personalized one-on-one telephone support by the firm. These results suggest that the information on the platforms facilitates learning by potential adopters thereby providing direct evidence of the learning mechanism (Ching, Erdem, and Keane 2013) often assumed in the marketing literature.

Our research contributes to the existing marketing discipline in the following ways. First, we show that low-cost social media tools can indeed facilitate adoption but also have some limitations. While our primary focus is on social media tools, we empirically compare and contrast the causal effects of multiple interventions on influencing adoption behavior in a controlled B2B environment. In this regard, previous literature has typically addressed one specific marketing tool and mostly in Business-to-Consumer (B2C) categories. Second, we try to understand multiple behavioral outcomes over the course of the adoption funnel and discuss the difficulties and possible solutions based on observations in the field and our data. Third, we disentangle the effect of a new type of influencer, the eminent village personality, from the effect of the social media platform by using a randomized controlled trial; we also provide suggestive evidence on the mechanism behind its influence. Finally, our research context is about new technology diffusion in developing areas which has not received much attention in the marketing literature. Taken together, we believe, our research shows one way in which marketing can have a positive impact on the world around us.

Conceptual Underpinnings and Relevant Literature

Uncertainties and Barriers to Adoption

From our interviews, we learned that when farmers are first exposed to a new technology, they need to decide whether to try it or not (we provide more insights in the field study in Web Appendix W2). At this stage, they face (i) uncertainty about the authenticity of the product and

credibility of the supplier; and (ii) uncertainty about the product's quality and its match value for their specific situations. These uncertainties are likely to hinder trial. If they decide to try, they need to make decision on how to use the technology, a decision typical in B2B markets (e.g., Hada, Grewal, and Lilien 2014). At this stage, they face (iii) uncertainty about how best to use the product most efficiently to get the maximum "bang for the buck." Their decisions on how to use the new technology will also affect their learning regarding product quality. In the final stage, based on the perceived value of the new product, customers decide whether or not to adopt the new product.

Resolving uncertainties and preventing misuse are therefore key to helping customers navigate the purchase funnel in B2B markets. These could be achieved by acquiring useful information. Normally, there are three ways to obtain information about a new technology: self-experimentation, from external sources including the innovating firm's support, or through social interactions with peers (e.g., Conley and Udry 2010; Bollinger and Gillingham 2012). Consequently, understanding how these different types of information affect trial, learning, and adoption behavior is critical.

Information from Usage and from Marketing Channels to Resolve Uncertainties

Self-experimentation and Usage. Self-experimentation is the most common way prospective customers learn about a new technology for those users who overcome the perceived risks and try the product. Even experienced users however, are often unable to use a technology appropriately which, in turn, limits their ability to appreciate a product's true quality. When using a technology, users face a slew of potential factors that might affect production and so cannot attend to all of them (Kahneman 1973): "their attention is limited while the number of potentially important variables is large." Therefore they can only pay attention to those variables they think are important and ignore variables that may be truly important to the production outcome; i.e., selective attention as in Schwartzstein (2014) and Hanna, Mullainathan, and Schwartzstein (2014). In our case, the pesticide solution needs to be of the right consistency (not too much or too little added water); the holes of the sprayer should be as small as possible for

obtaining better atomization results, etc. While self-experimentation is a useful benchmark, without the above knowledge, learning can be incomplete.

External Information – Social media platform. In emerging markets, information transmission is usually conveyed by in-person communication: discussion with neighbors (e.g., Conley and Udry 2010; Yamauchi 2007); training with agricultural extension agents (e.g., Birkhaeuser, Evenson, and Feder 1991; Bindlish and Evenson 1997, etc). Such methods are labor and resource intensive. Information transmission via word-of-mouth (WOM) takes time, leading to delayed adoption (Bollinger et al. 2019). Smartphone-based social media platforms provide a low-cost solution to enable peer effects by moving social interactions online, relaxing restrictions on time and distance required by face-to-face communication. It can also facilitate firm-customer communication through a "broadcast" function (Chen, De, and Hu 2015) in the sense that every message posted in the online platform can be received by all its members at the same time. In this paper we propose using an online social-media support platform to facilitate adoption.

External Information – Online Influencer. In conjunction with the social media support platform, another marketing intervention we consider is the online influencer. The idea of influencers as catalysts in innovation diffusion has been a key idea in marketing (e.g., Coleman, Katz, and Menzel 1957; Rogers 2003; Van den Bulte and Lilien 2001). Empirical studies have provided evidence on the role of influencers (e.g., Nair, Manchanda, and Bhatia 2010; Goldenberg et al. 2009; Libai, Muller, and Peres 2013; Godes and Mayzlin 2009; Hinz et al. 2011; Iyengar, Van den Bulte, and Valente 2011; Tucker 2008; Gong et al. 2017). Traditionally, influencers or opinion leaders are functionally defined as people who transmit new information about a product/idea to a group (Burt 1999). For example, physicians who prescribe a new drug share usage experiences about the drug with their colleagues (Coleman, Katz, and Menzel 1957).

However, the technology in our context is completely new to the market so none of the prospective users knows about its existence, let alone have any experience or knowledge in using it. So, in this paper, we explore the role of individuals that we refer to as "*eminent village personalities*." These influencers have two distinguishing characteristics. First, in the initial

stages of the diffusion process, they do not possess any extra information about the new product than the other prospective users. The second characteristic is that notwithstanding their lack of unique knowledge regarding this particular product, their opinions on a variety of topics are nevertheless respected by the prospective users. Later in our field work, we find that these influencers typically hold some village management responsibilities. This is consistent with observations of village leaders in developing countries who are frequently opinion leaders for a variety of topics, such as health, agriculture, and education (Rogers 2003). Eminent village personalities in our context bear some similarity to "market mavens" (Feick and Price 1987) who possess awareness and information on new products not only in a specific category but also across various categories. Eminent village personalities can be viewed as a generalization of the maven concept beyond marketplace activities to various aspects of farmers' lives.

Behavioral Predictions: Trial Stage

Bearden and Shimp (1982) note that a consumer's "willingness to try new products and evaluations of these products are related inversely to the amount of perceived risk." With our new technology, farmers face uncertainty regarding the credibility of the supplier/authenticity of the product, the risk of poor performance, and potential crop damage.[4] In trying to lower this risk, consumers look to information that is intrinsic to the product such as its attributes and functions. However, given the newness of our technology, such features are not informative; further, the supplier organization is unknown to the consumer. In such circumstances the user seeks external information to provide risk reduction (Olson and Jacoby 1972). At the pre-trial stage, external information made available through our marketing interventions all entail communications from an influencer or an individual in the social network. *So the level of trial will depend upon such interpersonal communications.*

Role of influencers. With influencers, the mechanism underlying the effect on trial if any, could come from a variety of sources.[5] (i) Referent influence or as French, Raven, and Cartwright (1959) note the belief that users want to be like the influencer and will be successful in doing so by behaving or believing as they do. (ii) Cultural evolutionary theory of credibility-enhancing

displays (CRED) (Henrich 2009) which demonstrates that the action of encouragement itself can enhance product credibility and encourage followers' cooperation. Even if the encouragement is not related to product features, it is *credibility enhancing* because dissemination of encouragement through the social media platform is costly to influencers: if the new product fails the reputation of the influencers will be hurt. In the absence of the influencer, it will be more difficult to resolve the uncertainty regarding authenticity and product quality.

Role of peers. Peer effects where trial by peers, conveyed on the platform, may affect one's own utility from trial (e.g., Banerjee 1992) as by mimicking others' activities, users may gain a sense of belonging and conformity (e.g., Bikhchandani, Hirshleifer, and Welch 1998). Alternatively, if peers provide information regarding product features, that might also encourage others to try the product by resolving uncertainty related to product authenticity and quality, and consequently, motivate trial.

Behavioral Predictions: Adoption Stage

To adopt the product, a key consideration for potential consumers is the perception of value (e.g., Gale and Wood 1994). Since the new technology was priced on par with pesticides currently on the market, price per se is unlikely to hinder adoption. The main route to resolving uncertainty related to quality and usage prior to adoption is *learning*. In the absence of any marketing interventions, part of the uncertainty might be resolved by learning through self-experimentation (e.g., Erdem and Keane 1996) - if the farmers experience positive outcomes after trial, they might be more inclined to adopt the new technology. Such learning may be incomplete because a negative outcome may stem not from the poor quality or match value of the product but due to incorrect usage. This is the third uncertainty discussed earlier.

Learning models (see Ching, Erdem, and Keane 2013, for a review) assume that users pay attention to their key production input variables and to the data from their experiences and those of others. Information obtained from each usage occasion provides a (noisy) signal of the true quality or match value of the product so users ultimately are able to achieve their "productivity frontiers," i.e., extract the most from their production inputs (in our case, the new pesticide) once

learning is complete (Hanna, Mullainathan, and Schwartzstein 2014). However, the productivity frontier is not guaranteed with a new technology [6] as some part of the knowledge associated with applying the technology is tacit, i.e., "not feasibly embedded and neither codifiable nor readily transferable" (*technological tacitness*) (Evenson and Westphal 1995). If prospective customers cannot appreciate the true benefit of the new technology they will abandon the product even after trial. Users on the social media platforms can however, learn from several sources. First, they can learn from communications from the firm (much like in traditional B2B one-on-one marketing). In the social media platform without influencer, social learning (Mobius and Rosenblat 2014) is also possible. The influencer per se, lacking the specific expertise required at this stage may not be able to provide additional inputs beyond those associated with social learning.

Context and Experimental Design

The Use of Pesticides in China and the New Technology

In this study, we focus on a new nanotechnology-based pesticide formulation (for short, the nano-pesticide) invented by scientists in a nanotechnology research lab in China. This new technology has two main advantages over conventional pesticides: 1) it is environmentally friendly and safe for users since it does not use toxic organic solvents; and 2) it has improved efficiency of application. Besides, the new pesticide can be used in the same way as traditional pesticides with no requirement for extra application instruments, such as water barrels and sprayers, lowering the users' switching costs. While the efficacy and safety of the nano-pesticide have been established by many national and international third-party double-blind lab and field tests, the question facing the developers was whether farmers would actually try and then adopt the technology. So while the pesticide awaits approvals from the government, the lab (the "firm") was interested in studying low-cost ways of reaching its customers - the farmers.

"One-Thousand-Farmers Trial (OTFT)" Program

In association with the firm we launched our "one-thousand-farmers trial (OTFT)" program that ran from April 2017 to August 2018. The aim was to recruit one thousand farming households, provide them with free samples of the new pesticide and get them to try and then adopt (i.e.,

order at the market price) the new technology. The program included two pilot studies and one field experiment. The first pilot study was conducted from April 2017 to February 2018 in Wuzhishan area, Hainan province, while the second one was from April to June 2018 in Zhijiang, Hubei province. We recruited 352 farmers from fifteen independent villages. The pilot studies helped achieve three goals. First, they helped us understand individual farmers' production practices and potential problems encountered while using the new pesticide. Based on this, we designed standardized guidelines for providing customized instructions on using the new technology to address specific questions such as how to adjust important input dimensions if the pest control outcome was not satisfactory, how to customize the application method for certain crop species (e.g. rice, vegetables, and cotton), etc. Second, as our experimental treatments involve social media support (and also personalized telephone assistance for comparison), adequate training for service providers with systematic and standardized protocols was critical. Third, especially for the second pilot study, we replicated our experimental procedure in a place similar to the location of the real experiment but geographically far away. This helped us test for feasibility in the local environment; it also enhanced external validity in terms of repeatability of program design and implementation (see Duflo, Glennerster, and Kremer 2007, for a detailed description of external validity of field experiments).

The main field experiment was conducted from June to August 2018 in Zaoyang Hubei province and involved 34 villages and 702 farmers (one farmer per household). Zaoyang is a county-level city located in northern Hubei province, China with a 1.44 million inhabitants and 1.4 billion USD in GDP. Located in a temperate zone (32.13 latitude and 112.75 longitude), Zaoyang is suitable for cultivating rice, wheat, cotton, and vegetables, which make it one of the "top ten crop production counties" in China (The City Government of Xiangyang 2020).

Design of the Experiment

Figure 1 shows the two levels of marketing interventions. The first level is the communication medium deployed to reach potential adopters: the social media support platform; traditional firm's one-on-one personalized customer support through telephone; and the self-

experimentation control group. The second level involves the deployment of eminent village personalities in the online environment. The sources of information corresponding to each treatment are shown in Figure 2.

[Insert Figure 1 and 2 about here]

Social Media Platform. For villages in our two social media treatments (one with influencers and one without), we form independent online discussion group/platform on WeChat for each village. Only farmers in the same village are invited to the village's discussion group. On the online platform, people can discuss any topic they want, not necessarily only related to the new pesticide. They can raise questions about the new pesticide or agriculture in general, which will be answered either by other farmers in the same discussion group or by the firm (represented by the researchers). Any information provided on the platform (i.e., from farmers and the firm) is available to all its members. Information on farmers' trial and adoption decisions are collected via follow-up surveys (described later).

Online Influencers. In around half of the social media treatment villages, we introduce eminent village personalities as influencers. Consistent with research in this area (e.g., Miller and Mobarak 2014; Nair, Manchanda, and Bhatia 2010; Van den Bulte and Lilien 2001), they are nominated by prospective users in the social network rather than appointed by the researchers. Influencers chosen usually have some responsibility related to village management. In Web Appendix W3, we provide a description of the influencers. Of the 8 influencers, 5 are village officers or party secretaries, 2 are village women's directors, and 3 are directors of plant protection stations. Those positions hold responsibilities for villagers' daily lives and welfare, such as agricultural production, poverty-reduction, birth-control, and heath care. Eminent village personalities are respected by farmers because of their positions and professional credentials. However, they do not have expertise with our new product per se.

In the initial week of the experiment, we encouraged the influencers to post messages to motivate other farmers on their platforms to try the new pesticide. Although not required to, we expect these influencers to respond (albeit differentially) to our encouragement as they are

relatively more advanced in their social networks and their village management duties entail helping farmers achieve better outcomes. Further, they may view this as a way of exercising thought leadership in the peer community. So we believe that our eminent village personalities view their roles as part of the advice they provide members of the community on a variety of different topics. Consequently we do not provide them with any monetary incentives.[7]

One challenge facing researchers is how to establish a causal relationship between influencers and the adoption process. Most existent marketing research studying effects of influencers use observational (i.e., nonexperimental) data where the effect of influencers is confounded with the effect of networks. Therefore we decided to take an experimental approach instead. Our experimental design is inspired by Peer Encouragement Designs as in Eckles, Kizilcec, and Bakshy (2016), Aral and Walker (2012), Banerjee et al. (2013). In Peer Encouragement Designs, an peers are randomly assigned to an encouragement to behavior which can increase or decrease the chances of those peers engaging in specific behaviors. One can then observe how this encouragement induces endogenous behavior in the network and consequently, measure how peer effects influence outcomes. Compared with using observational data, running experiments, such as Peer Encouragement Designs, can effectively avoid the presence of confounding due to homophily and common external causes (e.g. Manski 1993; Shalizi and Thomas 2011; McPherson, Smith-Lovin, and Cook 2001; Manski 2000). In our context, we introduce influencers as an encouragement to induce endogenous online social interactions, and consequently trial and adoption decisions of the new technology. Importantly, we have 2 other conditions that help us isolate the effects of the influencers - a condition with the social network but without the influencer and another with neither. Together, these three conditions make our experiment unique while allowing us to isolate the effects of the various interventions.

Firm Initiated Customized Support. One-on-one support is provided to farmers through telephones during follow-up surveys starting with the first two weeks after the start of the trial (this group gets no interventions till then). In each survey, the support personnel remind those who have not tried to do so and learn how the farmers are using the pesticide to address any

questions/concerns. All the information provided follows standardized instruction guidelines (see Table W4-1 in the Web Appendix). Only the contacted farmer gets her customized instructions. This approach is expensive to implement because it involves a two-way communication where each farmer has the opportunity to engage with the service provider. Since the first interaction occurs during the first follow-up survey, we do not expect farmers in this treatment condition to be different from those in the control group (only self-experimentation) at the time of the first survey in terms of trial behavior.

The Agricultural Environment and Experimental Set-up

There are three specific features of the agricultural environment and farmer behavior that have implications for the design and implementation of our field experiment. In our field experiment, we focus on farmers living in the same growing region to mitigate concerns regarding the impact of spatial heterogeneity on agricultural practice (e.g., Carter, Laajaj, and Yang 2014; Glennerster and Suri 2015; Suri 2011). Next, we require that all research tasks and information collection be completed within the same planting season to mitigate the effects of seasonality and unpredictable weather patterns (De Janvry, Sadoulet, and Suri 2017). Third, our observational period has to be in line with the pest control cycle since being too late or too early could significantly affect a farmer's willingness to try or adopt a pesticide.

In order to investigate the impact of social media via a randomized controlled trial and to avoid contamination across treatment units, we need to use independent, naturally formed, and geographically separated social networks, such as villages, as our observational units. Fortunately, Zaoyang is a large agricultural area with around 160 agriculture-based villages. With the endorsement of the local (official) agricultural department, we selected 34 villages that are very similar in terms of geographical features, production conditions, income levels, culture, language, and other factors. Farmers in these areas plant rice as their main crop and face the same schedule for seeding, irrigation, pest control, and harvesting.

Figure 3 shows the timeline of the main experiment. On the first day, the experiment began with an information session. Since a requirement of the village (government) officers was that all

farmers in the village should have the opportunity to participate in the study, the announcement of the information session was made on the village's public address system the day before the session in all villages in this study. Village officers were not privy to any information regarding the specific treatment group that the village was in. Consequently, we do not face an issue of differential selection into the treatment groups. By focusing on those who then show interest in the experiment helps control for heterogeneity along unobserved dimensions, such as the effort that users are willing to put into the new technology (De Janvry, Sadoulet, and Suri 2017). Between 14 and 30 farmers showed up in each village to attend the information session conducted by the researchers. During the information session, our researchers gave a 15 minute introduction on the features of the new pesticide technology, including background information and the basic application methods. Participants were required to fill out a baseline survey for collecting information on their demographics and farming practices. Extended surveys to a subset of farmers (described later) were then administered.

[Insert Figure 3 about here]

After the baseline survey, free samples of the new pesticide, sufficient for 1,333 square meters of crops or vegetables were distributed. Farmers in villages assigned to the two social media treatments were then invited to join a social media discussion group formed for their specific village by scanning a QRcode using WeChat. During the information session of a village in the treatment of social media with influencers, we asked farmers to nominate one person as the group leader (the eminent village personality) in the discussion group. The next two months were the observation period. We conducted three follow-up surveys every two weeks to collect information on each farmer's production inputs and outcomes if they tried the new pesticide, satisfaction levels, etc. During the last follow-up survey, researchers asked farmers whether they were willing to adopt this new technology or not by offering them an opportunity to order the product at the market price. We asked the farmers who decided to order to put down 20% of the price of their order and their government issued personal identification numbers as collateral.

Since the pesticide could only be used in the next planting season putting down a partial payment in advance can be seen as a strong commitment towards future use.

Data Description

Of the 702 farmers, 59 were deleted from our final sample for the following reasons: (i) farmers decided to work in cities and did not farm this year; (ii) farmers left the wrong contact numbers and were untraceable, and (iii) farmers used identical contact persons. This left us with 643 farmers as individual units in our sample.

We also observe communications on WeChat, the social media platform. During the study period, farmers in the two social media treatments could freely communicate on their villages' social media discussion groups. Messages posted included photos or videos of pesticide application and other types of discussions: asking questions, describing usage experiences, replying to others' questions or comments, and instructions given by the firm (see Figure W4-2 and W4-3 in the Web Appendix for examples). To collect this type of information, we downloaded all messages posted on each village's WeChat group. We then manually categorized those messages into one of the following: 1) information format (e.g., video, audio, text, and emoji); 2) information content reflected in seven different topics (e.g., new pesticide and trial program related, agricultural, and non-agricultural related topics); 3) sentiment conveyed in a message: positive (e.g., praise for the product), neutral, or negative (e.g., complaints).

Table 1 provides the descriptives of the main characteristics of the farmers. About 65.8% of farmers in the main sample are men. The average farmer in the study was approximately 51 years old, middle-school educated, and has two members farming in the family. The average percentage of farmers who own arable land more than 3.3 acres is around 40%, inline with the trend of transforming from small-farm planters to larger planters in rural China (Business News 2018). Approximately 20% of farmers are or used to be village officials. In Web Appendix W5, we provide balance checks across treatments and the control group. As illustrated there, only 4 out of 36 comparisons we consider are significant, which could be due to chance.

[Insert Table 1 about here]

For the eminent village personalities, we found that the average age is around 46 years, indicating that they are younger than the average farmer in our sample (around 51). Besides, they are better educated (high school or above) than the average farmer (middle school to high school). In terms of other characteristics such as the number of family members who farm and size of farmland, the influencers are similar to the entire sample (see Web Appendix W3).

A unique feature of our interventions is the use of social media platforms and the ability to study the nature of online interactions. Before we present our main findings, we first describe the volume, topics, and valence of the online conversations. Figure 4 shows the evolution of social interactions on social media platforms of villages in the two treatments of social media support platforms. We find that social media with influencers creates more messages than social media alone treatment in terms of both the total number of messages (136.2 (SD = 39.02) vs 68.0 (SD = 38.78)) and messages per person (M = 7.39 (SD = 3.19) vs M = 4.31 (SD = 1.15)) (significant at the 1% level). Additionally, we check to see whether online influencers are creating the bulk of the comments on the social media platform and find that the average percentage of messages created by them is just around 8.8% (SD = 3.78%) which means that most of the discussion is being generated by other prospective users.

[Insert Figure 4 about here]

Summary statistics of message topics are in Table 2. We find that farmers in the online influencer treatment are more willing to post evidence regarding their application of the pesticides than are farmers in social media alone treatment (see the first row of Table 2). The former group of farmers is more active in discussing the new technology and trial program-related topics (see the second through the sixth rows of Table 2) than their counterparts in social media alone treatment. Also, in social media alone treatment more posted messages concern topics unrelated to the new pesticide, such as news and jokes. A similar pattern may also be found over time in Figure 5. This indicates that eminent village personalities help create a better online discussion environment that fosters more active and relevant online social interactions.

Finally, we also categorize the valence of the content of the posts. We found that the proportion of positive messages created in social media with influencers treatment is 0.063, while the one for social media alone treatment is 0.012 (significant at the 10% level). Besides, there is no difference between the two social media treatments in terms of neutral and negative messages.

[Insert Table 2 and Figure 5 about here]

Findings

The focus on social networks as the units of analysis constrained our ability to work with a large number of villages. We recognize that the small sample size (34 villages) makes identifying significant effects difficult. Even so, as we show below, we obtain statistically significant results as reflected in different parametric and non-parametric tests. In this section, we present results on our key behavioral outcomes, trial and adoption behaviors. In the next section we discuss the possible mechanisms behind the influence of different marketing interventions.

Trial and Adoption Behaviors: Village-level Analysis

Table 3 shows regression results for dependent variables defined at the village-level 1) early (during the first 2 weeks) and final or cumulative (during all 8 weeks) trial rates (proportions of sample farmers trying), 2) adoption rates (after 8 weeks; proportions adopting), and 3) conditional adoption rates (ratio of adopters to triers). The independent variables are indicators for the various marketing interventions. The base condition is the self-experimentation control group. The differences across treatment groups are critical in our analysis. However, standard asymptotic tests can over-reject when the number of clusters is small (5 to 30). Hence, we adopt the cluster bootstrap-t procedure (see bottom panel of Table 3) which can provide asymptotic refinement (Cameron, Gelbach, and Miller 2008).

In the first and second columns of Table 3, the dependent variable is early trial rate. We find that the social media platform that includes an influencer shows the highest mean early trial rate across villages. This indicates that when everyone is unfamiliar with the new technology, eminent village personality can significantly positively influence trial behavior, overcoming the first type of uncertainty over authenticity and supplier credibility. We also see that social media

alone treatment does not outperform the control group, the control self-experimentation condition. Since we provide identical online firm's support in the form of "broadcast" messages (e.g., welcome message and reminders) during the first 2 weeks on every village's social media platform, such information by itself may not be powerful enough in overcoming farmers' uncertainties. Note that our firm initiated one-on-one customer support was only launched right after the second week of the experiment (during and after the first follow-up survey), meaning that there was no difference between the firm's one-on-one support treatment and the control group as expected without any external information sources.

[Insert Table 3 about here]

The third to fourth columns show results when the cumulative trial rates are the dependent variables. Interestingly, we find that social media platform with influencers again outperforms social media alone treatment and the control group, with social media alone treatment not showing a statistically significant difference from the control group. This confirms the previous finding that the social media platform alone cannot foster peer effects as expected, shaping our understanding on online social influence in the absence of a way to overcome the uncertainty regarding product authenticity and supplier credibility. The performance of firm's one-on-one support treatment demonstrates the persuasive role of personalized firm initiated support in overcoming the uncertainty regarding authenticity.

The fifth to sixth columns use adoption rate as the dependent variable. Marketing interventions that use social media platform, regardless the presence of influencers, outperform the self-experimentation (and any offline social interactions) only control condition. Further, social media platform with influencers shows a significantly higher adoption rate than social media alone treatment. Nevertheless, these findings indicate potential learning effects from using the social media support platform on the final adoption behaviors of farmers. Additionally, since all the marketing interventions involve some external support from the firm, this could also reflect the usefulness of firm's assistance for B2B customers. Finally, the firm initiated one-on-one support does as well as social media with influencers in terms of adoption.

From the last two columns, we see that all marketing interventions show significant effects in improving the adoption rate among farmers who tried the new technology (for brevity, we call it conditional adoption rate (CAR) in the following text), suggesting the presence of some forms of learning. Besides, the CARs of the three marketing treatments are not significantly different from each other. This implies once farmers in the social media alone treatment try the pesticide, the additional external information available significantly influences their adoption. And given similar trial rates as the control group, this implies that some external information is required even after trial to convince farmers to adopt.[8]

Robustness checks. We also conducted a number of robustness checks of our findings. The first is that as dependent variables, we used the raw numbers of people who tried and adopted instead of using village-level proportions. The benefit of doing this is that it avoids the potential influence of heavier trial and adoption rates in villages with fewer sample farmers from biasing our results. Table W6-1 in the Web Appendix shows the results. We find that all the key differences are significant and consistent with the previous analysis. Next, to further assess statistical significance, we conducted a permutation test, a nonparametric method, as in Bloom et al. (2013). Different from the traditional tests which rely on asymptotic arguments along the cross-sectional dimension (here, the number of villages) to justify the normal approximation, permutation tests do not rely on asymptotic approximations. They are based on the fact that order statistics are sufficient and complete to produce critical values for test statistics. Since the comparison between treatment groups and the control group are obviously significant even in asymptotic tests, we only present the results of the differences across various treatments from permutation tests in Table W6-2 in the Web Appendix. We also provide a detailed illustration of this test in Web Appendix W6. We see that all the differences across treatment groups are significant as in the previous regression analysis.

Trial and Adoption Behaviors: Individual-level Analysis

The literature involving social networks and adoption often leverages individual-level data despite the likely correlation in decisions across members of the network. Such studies include

Miller and Mobarak (2014), BenYishay and Mobarak (2014), Beaman et al. (2016), and Banerjee et al. (2013). Most of these studies perform individual level analyses based on a conditional independence assumption: i.e., conditional on being in each treatment group (and all the factors influencing trial and adoption therein), any unobservable factors influencing the individuals' decisions are independent across individuals. So the treatment dummy encompasses those unobserved factors influencing behavior that might induce correlations across individuals. Under this rather strict assumption, we can run individual-level (logit) analyses by controlling for covariates and clustering standard errors. We present these results in Table W6-3 in the Web Appendix which replicate our findings from the group-level analysis.

Customer heterogeneity and adoption behavior. At the time of our baseline data collection, in addition to the information collected in that survey, we were able to collect additional information from about 75% of our sample farmers. It was not possible to collect these data from all of them because the village officers imposed constraints on how long we could talk to them based on the time of day that the specific farmer was interviewed in that village (the officers did not want the farmers distracted from productive work). Thus participation in the extended survey can be assumed to be at random and we verified this by comparing their characteristics to the full sample. A list of these variables and the specific questions are in Web Appendix W7.

In this section, we use the additional variables as covariates and moderators to study how customer heterogeneity affects adoption or moderate the effects of different marketing interventions on adoption. Given space constraints, we focus here on the outcome that ultimately is of most interest, i.e., adoption. The results are in Table 4. Overall, in terms of model fit, including these variables seems to be adding no incremental explanatory power looking at either AIC or BIC. The main effects of most of the additional variables are estimated imprecisely and are not statistically different from zero under conventional levels. However, there is one exception: we find that users with larger farms are more likely to adopt the new technology than smaller farmers. Further, our moderation analyses reveal a few patterns. First, the variable "farmers think the most important factor influencing their pesticide purchase decision is price"

has a negative interaction with the social media treatments, suggesting that people who are more price sensitive will benefit less from the social media treatments (than the control group). Further, the interactions between the three treatments and the dummy "farmers think the most important factor influencing their pesticide purchase decision is user safety or health hazard" are positive and statistically significant for all marketing treatments. This, along with the negative main effect (indicating that those for whom health issues are important are least likely to adopt), suggests that all our marketing interventions are able to overcome the baseline lower level of adoption by such farmers. Finally, older farmers benefit significantly more from the one-on-one customized firm assistance through the telephone than younger farmers, i.e., the traditional communication method does better in assisting older customers.

Robustness checks. It is important to note that with nonlinear models like the logit, computing and interpreting statistically significant interactions is not as straightforward as in linear models (Hoetker 2007, Ai and Norton 2003). We conducted robustness checks using the "inteff" procedure in Stata mentioned in Norton, Wang, and Ai (2004) to compute the marginal effects and statistical significance of the interaction terms in our logit analyses. The results indicate that our inferences based on the interaction terms are robust.

[Insert Table 4 about here]

Interpreting the results. Our above findings are in line with previous behavioral studies. Consumer researchers (e.g., Celsi and Olson 1988; Zaichkowsky 1985; Mitchell 1979) have hypothesized that personal relevance of a product is represented by "the perceived linkage between an individual's needs, goals, and values (self-knowledge) and their product knowledge (attributes and benefits)." If "product characteristics are associated with personal goals and values, the consumer will experience strong feelings of personal relevance or involvement with the product" (Celsi and Olson 1988). In our context, the most important attribute we promote is the non-toxic nature of the pesticide. People who value health (price) more will have a stronger (weaker) feeling of personal relevance or involvement with the product. As personal relevance or involvement (motivation to process) is directly related to attention and comprehension (Celsi and

Olson 1988) and effort spent toward purchasing a product (Clarke and Belk 1979), farmers who value health (price) more are more (less) likely to be influenced by the marketing treatments.

Mechanisms

In this section we provide some suggestive evidence for the potential mechanisms that might underlie our findings above. Since the evidence is correlational, we cannot make causal claims. Nevertheless, we feel that the information does provide insight into what might be going on.

Trial behavior

During the first two weeks of the experiment, we find that the social media with influencers treatment outperforms social media alone treatment. What might be the mechanism underlying this difference? One explanation is trust building and credibility enhancing through referent influence by influencers via words of encouragement and mentioning their own usage (Merton and Merton 1968; French, Raven, and Cartwright 1959; Henrich 2009). An alternative explanation is through effective online social learning, where peers (non-influencers) provide information on their own trial and usage experience and directly affect a farmer's knowledge about the new product (Conley and Udry 2010).

Online word-of-mouth and trial behavior. For suggestive evidence on online social learning, we look at what happened on the social network. First, we observe that influencers posted encouraging messages online (see Table W8-1 in the Web Appendix) in the initial stage of the intervention (e.g., the influencer from a village posted "Hello, my farmer friends! Recently the weather is good for pest control. Please use the new pesticide from.... Don't forget to post your application photos."). On average, while influencers post 4.4 encouraging messages in the first 2 weeks, 5 influencers posted 2.4 messages regarding their own trial. Further, Table 5 shows a summary of messages generated by farmers (excluding influencers) during the first two weeks (before the first survey) and the other weeks of the experiment. We categorize messages into three types based on their content. The first type contains messages directly related to description of effectiveness of the new pesticide; the second one contains all the other messages related to the new pesticide and the trial program; and the third one contains messages on unrelated topics.

We find that during the first two weeks of our experiment very few messages address the new pesticide or the trial program. The total average number per village is less than three, and there is no significant difference between social media with influencers and social media alone treatment. Meanwhile, the number of messages related to product efficacy is even smaller. Thus, online social learning (Mobius and Rosenblat 2014) from peers (non-influencers) is less likely to drive early trial behavior through enhancing the knowledge base of the new technology.

Taken together, we see that the difference between the two conditions is not in terms of the online behavior of non-influencers but in the social media with influencers treatment reflecting encouragement and usage messages by the influencers. We take this as suggestive of the impact of eminent village personalities on initial trial behavior through trust building for the new technology, the supplier, and the trial program, thereby alleviating the first type of uncertainty referred to earlier in the paper. To show the correlation more formally, we estimated a logit model of non-influencer villagers' early trial decisions (1/0) with the number of encouraging messages, whether the messages include usage experiences of the influencer, and other controls in the social media with influencers condition (see Table W8-2 in the Web Appendix). We find that encouragement reflecting usage experience has a strong and significant positive correlation with early trial behavior.

[Insert Table 5 about here]

From the third week on, the volume of the new technology related discussions increased rapidly (see both Table 5 and Figure 5). At the same time, the risk mitigation effect of the influencer diminished, as fewer encouraging messages were posted by them (see Table W8-1 in the Web Appendix). To show some correlational evidence between trial behaviors and online activities, we look at the decisions of non-influencer farmers to try the pesticide during the 8-week duration in the two social media support conditions as a function of the number of pesticide-related messages posted by non-influencers. We have a common intercept but a treatment-specific coefficient for the number of messages. We find that the number of related

messages has a positive and statistically significantly correlation with cumulative trial, but only in the social media with influencers condition (see Table W8-3 in the Web Appendix).

The role of eminent village personalities and social media platform on trial behavior. These results suggest that the eminent village personalities facilitate diffusion in two ways. First, they can directly motivate the initial use of a new technology by mitigating risk in the early stages by engendering trust. Second, they act as catalysts for online social interactions by others, thereby indirectly influencing the diffusion process. We conjecture that the early trial due to influencer engagement results in these triers contributing to online WOM. As the interactions among prospective users continue to evolve and propagate by themselves, those online interactions motivate more people to try the product. This larger base of users who have tried and experienced the product ultimately results in adoption and diffusion of the new technology. At the same time, for farmers who have already tried the pesticide, the presence of eminent village personalities appears to have no direct effect on final adoption behavior as information at this stage comes from peers or from the firm's broadcast information. Indicative evidence for this can be seen in the similar conditional adoption rates across the two social media treatment conditions.

Another important lesson learned from the above analysis is that using a social media platform cannot automatically create the desired social interactions or change prospective users' behaviors vis-*à*-vis the new technology when there is uncertainty upfront about product authenticity and supplier credibility. This finding provides firms with insights on how to operate a successful social media communication channel. Although social media platform is a compelling marketing tool, only creating such an online environment is far from adequate. In order to create product-relevant online discussion and finally propel diffusion of a new product or a new idea, our study suggests motivating initial trial by inviting an effective influencer to "jump start" relevant online interactions. To generalize this finding further, we note that it is important for the initial triers to actually participate on the platform. In contexts where this is likely, our approach would have a greater chance of success. In the absence of the online discussion emanating from trial, we are unlikely to find the level of success as in our experiment.

This finding resembles the evidence documented in Gong et al. (2017) in the context of tweeting, where the authors find that influential retweets can increase show viewership directly if they are informative, and indirectly by attracting new followers to the show's media company.

Traditional one-on-one customer service and trial behavior. For the one-on-one customized telephone support condition, based on the logs maintained by the support staff, we categorized the calls as being focused on one of Product-related, Risk-related (harm to crops or product authenticity), and Price- and Purchase-related. At the end of the first 2-weeks (when the first set of calls occurred) a majority of the calls (61 percent) were related to risk, followed by product (38 percent). However in subsequent weeks, the calls shifted to product-related issues (83 percent). Importantly we find that a logit analysis of individual trial on call duration (and controlling for demographics, i.e., older farmers need longer call durations) shows a strong positive correlation between duration and trial behavior. In this case, using the terminology of French, Raven, and Cartwright (1959), it appears that the firm's expert influence facilitates trial by the farmers.

Adoption behavior and learning outcomes

In our conceptual underpinnings section, we noted that adoption requires farmers to resolve their uncertainties regarding quality and usage. In other words, they need to learn about the product's characteristics such as effectiveness and harm to crops and about its usage. To this end, we asked farmers who tried the new pesticide for their evaluations of the benefits of the new technology and usefulness of the trial program in the final survey. We asked the following questions: 1) "Comparing the new pesticide with the one you used before do you think the new technology shows better results in: i) pest control effectiveness, ii) harm to crops, and iii) pesticide usage reduction." and 2) "Do you agree/disagree with the following statement: the trial program helped me obtain useful information and knowledge about the new technology." Answers to both questions are measured on five-point scales, where 1 = Strongly Disagree and 5 = Strongly Agree. This approach of measuring learning outcomes directly is a unique feature of our paper,

as most learning papers infer that learning occurred from trial/adoption outcomes (see Ching, Erdem, and Keane 2013, for a discussion).

We first calculate a treatment-level "satisfaction" measure as the proportion of farmers who provided a rating of Agree (rating = 4) or Strongly Agree (rating = 5). Table 6 shows these results. We see that the learning measures are highest for social media with influencers treatment (and firm's one-on-one support treatment) for the product feature of "effectiveness of pest control" and "pesticide usage reduction." The product attribute, "harm to crops," is harder to define as compared to the other two product attributes. Interestingly, we found that the firm's one-on-one support, is more effective in promoting understanding and satisfaction for this "opaque" attribute, indicating the superior nature of personal interactions between the firm and prospective users in communicating vague product features. The last two columns are related to the overall evaluation of the usefulness of the program. It shows that the social media-based treatments outperform the control group, which is consistent with the results we observed in the previous sections. The traditional marketing approach also performs well.

[Insert Table 6 about here]

To correlate the marketing interventions more formally with measured knowledge and learning of the new pesticide's attributes, Table 7 shows the results of an individual-level ordered logit regression (given the 5-point measurement scales described above) with village-level clustered standard errors. Our sample focuses on farmers who have tried the new technology during the experiment and so our results should be interpreted with some caution since the farmers who tried did so as a consequence of receiving different treatments. The dependent variables are the measures on beliefs (learning) regarding the three product benefits. In model (1) and (3) where the DVs are learning measures on product effectiveness and usage reduction, all three marketing interventions are significantly higher than the control group, meaning that the lower-cost social media based tools help improve understanding of product efficacy and usage amount. Harm to crops is the most difficult product feature to learn in our context. Among the three marketing interventions, one-on-one support on the telephone is strongly correlated with

improving learning outcomes for all attributes. We also find that individuals who have served as village officials are more likely to have a higher evaluation of product effectiveness and reduction in usage amount, indicating some heterogeneity in appreciating the new technology.

[Insert Table 7 about here]

We conducted a "process analysis" to investigate whether learning about product features mediates the effects of marketing interventions on adoption. Such an analysis is often used in consumer behavior research for investigating underlying behavioral mechanisms but is not common with survey variables (an exception being Bollinger et al. (2019)). [9] We employed a bootstrapping procedure described by Imai, Keele, and Tingley (2010). This approach includes procedures that compute a 95% confidence interval (CI) around the indirect effect (with 5,000 resamples). If a CI does not contain zero, it suggests mediation. A mediation analysis using indicator of social media with influencers treatment as the independent variable, adoption as the dependent variable, and learning measure on product efficacy as the mediator revealed a significant effect of learning (estimated coefficient = 0.07, 95% CI = [0.020, 0.126]). Two similar analyses using social media alone and firm's one-on-one support as independent variables reveal a similar pattern of findings that product efficacy underlies the effect of social media alone treatment (estimated coefficient = 0.088, 95% CI = [0.010 , 0.176]) and firm's one-on-one support (estimated coefficient = 0.040, 95% CI = [0.010, 0.079]), providing evidence that product efficacy learning mediated the effects of the three interventions on adoption.

We then conducted a set of mediation analyses using the measure for crop damage prevention as the mediator and found no significant effects for social media with influencers treatment (estimated coefficient = 0.004, 95% CI = [-0.015, 0.025]) and social media alone treatment (estimated coefficient = 0.003, 95% CI = [-0.024, 0.034]), whereas the effect of the firm's one-on-one support on adoption are mediated by harm to crops learning (estimated coefficient = 0.047, 95% CI = [0.004 , 0.098]). A similar set of analyses using the measure for usage reduction as the mediator revealed that this feature mediated the effects of the social media interventions (and firm's one-on-one support as well) on adoption (for social media with

influencers treatment, estimated coefficient = 0.095, 95% CI = [0.042, 0.151]; for social media alone treatment, estimated coefficient = 0.098, 95% CI = [0.0171, 0.185]; for firm's one-on-one support, estimated coefficient = 0.060, 95% CI = [0.002, 0.108]), providing further support for our explanation that learning about product features might underlie our effects. These findings provide suggestive empirical evidence that learning was facilitated by our social media interventions which could then have led to adoption by the farmers.

Cost analysis and economic good

In emerging markets, the public sector or NGOs play a major role in promoting new technologies and miracle drugs, such as new farming technologies and cures for a variety of illnesses. For these organizations, social welfare is the primary goal rather than the earning of profits. Therefore, sustainability has been hard to achieve with such public programs (Kremer and Miguel 2007). However, for the private sector that strives to promote socially beneficial new products and create a better world, business sustainability and profitability are also paramount. Therefore, adopting the perspective of a company, we compare the costs of the different marketing interventions. To mimic the "real world," we paid our research assistants who served as the firm's representatives in all three marketing interventions more than the market wage that the firm would have paid had it done the implementation. This way, we believe we paint a conservative picture of the costs associated with the various interventions. We calculate the return on investment (ROI) as total revenue (calculated based on the market price) earned from each treatment minus its corresponding costs then divided by costs. We find that social media with influencers is the most cost-efficient way with the highest ROI value (3.45), followed by social media alone treatment (2.45).[10] Although the traditional marketing approach is effective in promoting trial behavior and learning performance, it is the most expensive (ROI = 1.91) among the three marketing interventions. In general, marketing interventions brought an averaged increase in adoption rate by 30%, compared to the control group. This may lead to a total increase of productivity by 6% and reduction in production costs on pesticides by 20% (both twice as large as for the control group). In the long run, the potential benefits to the environment

and to people's health brought about by the new green pesticide technology is large. The detailed description on the cost analysis can be found in Web Appendix W9.

Discussion

Many technologies even with obvious advantages have not been widely adopted in developing and emerging markets where they are urgently needed. Specifically, we investigated how to deploy online social media tools to alleviate customer uncertainty and to promote the adoption of a new non-toxic and eco-friendly pesticide in China. We contribute to the marketing literature in several unique ways. First, we consider three types of uncertainty facing potential adopters. These include: 1) the authenticity of the new product and the supplier's credibility; 2) the "objective" quality or the "match value" of the product; and 3) how best to use or apply the technology in order to get the best outcomes from it. Second, we consider multiple behavioral outcomes along the adoption funnel including trial in the initial stages after introduction, subsequent trial behavior, and ultimate adoption. Finally, we examine the role of a new type of influencer, eminent village personalities, whose opinions, like market mavens, are valued across a broad set of topics, even if they lack expertise specific to the new product. Together, our research provides new insights to research on B2B marketing and on ways in which marketers can help create a "better world."

A key insight is that even in a rural setting of an erstwhile emerging market, social media influencers can offer an effective way of promoting the adoption of a "better" new B2B product. Influencers play a key role in dispelling concerns regarding the credibility of the new product early in the adoption cycle; a function critical for the eventual success of that medium. Ultimately, the combination of information sources on the platform promote learning about the features of the new product and alleviate uncertainty associated with product quality and how best to use the new product in order to achieve best outcomes from it. At the same time, it also points to why the social media support platform by itself falls short of the performance of traditional B2B one-on-one marketing support in the purchase funnel.

Implications for practitioners

We highlight three important implications for practitioners. First, social media can provide effective, low cost means of reaching, communicating, and convincing potential adopters of new technologies in otherwise difficult to reach markets that are nevertheless crucial for long term success. Second, when promoting a new product in these markets, it is crucial to take into account the entire purchase funnel rather than focusing on just one specific action, such as trial or final purchase behavior. Indeed, a critical stumbling block is early in the process where potential consumers may not engage due to concerns about the product's and the firm's credibility. Third, businesses, especially in the technology sector, have embraced the use of field experiments to guide their thinking and decision making about various marketing levers that might be used to grow their businesses. Our study provides evidence that even in rural environments, experiments might be a valuable tool for practitioners. Our experiment, conducted in collaboration with local governments, demonstrates how practitioners seeking "better world" outcomes can avoid higher cost marketing interventions in favor of low cost and readily available tools.

Our findings provide insights for managers and policy makers who aim to leverage marketing for doing good in the world. To do good, marketers need to convince consumers to adopt products that are good. Important barriers to such adoption are the uncertainties associated with the product and the inability to learn about the features and benefits of the product. We addressed these issues by understanding the entire process of adoption. When a product is brand new to the world, encouraging trial behavior among prospective users is key. During this stage, overcoming uncertainty about whether the new product is authentic or not is paramount. We document that an influencer, albeit one not familiar with the new technology, works well in an online social media environment to encourage followers to try the new product. At the same time,

traditional firm initiated customized service and support has a significant effect in motivating

trial behavior. Both these approaches also lead to improved outcomes in the adoption stage but

via different routes. On the social media platform, the ability to exchange information between

the triers and information provided via broadcast by the firm promote learning about specific

benefits of the product as well as the best ways to use it. The more traditional marketing

approach also accomplishes these objectives but via one-on-one communication between the

firm and the potential customer. For marketing to do good, it also needs to do it at scale to have a

wider impact. The social media platform with an influencer wins out here because it is more

cost-effective than one-on-one marketing by the firm.

Our results also suggest that practitioners should think carefully about how to use social

media most efficiently. Although research has documented its use for changing consumer

behavior, it is not a panacea and requires careful management. Specifically, at the trial stage of

the funnel we see the platform underperforming because it cannot, by itself, resolve uncertainty

regarding supplier credibility and product authenticity. The lesson that needs to be learned is that

creating an online social media platform does not guarantee peer effects as desired. We also offer

a solution to this funnel-holdup problem - having an influencer who can vouch for the credibility

of the product, and who tries out the product and reports it on the platform. The influencers do

not need to have expertise specific to the new product. They just need to be eminent persons in

the offline world, such as village officers or women directors in our context, whose opinions are

respected and well perceived by others. We find that the presence of an influencer relative to not

having one on the platform creates an online environment which fosters more product-relevant

discussions among participants. Those discussions on products then motivate learning toward the

new product. So influencers who are well-known only in an offline context can nevertheless help

promote adoption through online tools. Without the presence of an influencer, a social media platform is only beneficial to people who are intrinsically more interested in trying out the new product.

Implications for researchers

We provide three key implications for researchers. French and Raven (1960) among others, have described the different types of power that influence others such as legitimate, reward, coercive, referent, expert, and information. From a theoretical perspective our findings provide suggestive evidence for referent influence as being the route through which the influencer plays a role in the adoption process. Different from traditional view in marketing literature that influencers need to have new product relevant expertise in order to exerts their influence, our findings point out that personnel who is eminent in an offline contexts, although not having expertise or knowledge specific to the new product, can also have influence in promoting adoption through online tools. Such effect is consistent with credibility signaling on social media and its consequences for new product trial. In situations with a large number of new products entering the market, we view this finding as potentially generalizable beyond our current context. Future research can further endeavor to establish the causal link in a more systematic matter.

A second implication of our findings is that we now have direct empirical evidence on how information on the social media platforms facilitates learning and how this learning might potentially be a route to new product adoption. While previous research has embraced the idea that resolving uncertainty via learning is key to product adoption and use, little direct evidence existed on the mechanism. Going further however, our research also underscores the potential limitations of different information mechanisms to resolve the uncertainty. By measuring how learning occurs under each information mechanism along the different attributes or benefits associated with the new product, our research highlights the importance of understanding the linkage between information sources and their ability to resolve uncertainty. Our results point to the social media platform (even with an influencer) not being able to fully communicate all the

product features. Specifically, on the important dimension of crop damage, farmers in these interventions do no better than in the control group. A key takeaway for researchers is to try and understand the specific barriers to learning associated with the social media platform and approaches to overcoming them. Alternatively, a hybrid approach in which the social media platform identifies specific users that then need to receive one-on-one firm intervention may be useful to pursue. Understanding the efficacy and cost-effectiveness of such approaches may be a worthwhile future research endeavor.

A third implication is more methodological in nature. While time and resource heavy, field experiments allow quantitative marketing researchers to obtain mechanism-related insights that are otherwise difficult to obtain using only observational data. Such insights can then feed into building richer theoretical models of behavior. Given the importance of understanding behavior and the role of marketing in it, we encourage researchers to invest effort in the field and conduct more groundwork while engaged in such studies. The real world is more complicated to understand than just digging into existing data "....through the accumulation of a set of small steps, each well thought out, carefully tested, and judiciously implemented" (Banerjee and Duflo 2011), we hope marketing can do better at doing good. We are excited at the possibility that field experiments with a variety of different marketing tools can help fight poverty, disease, and pollution and contribute to the development of economies the world over.

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Notes

[1]While one can argue that dosage and compliance are important for pharmaceutical products that have been heavily researched, e.g., Ching and Ishihara (2010), these can be learned by the physician over time.

[2]Note that self-experimentation pre-supposes trial implying that it is not relevant for the resolving uncertainty regarding authenticity and supplier credibility.

[3]We view the pesticide market as a B2B sell as the efficacy of the pesticide influences the livelihoods of the farmers and because of the various types of uncertainties associated with its adoption is typical of B2B rather than B2C markets. Nevertheless, we acknowledge that some readers may view the product as being more like a consumer product.

[4]In our case since trial involved only the use of the free samples we provided, cost considerations are not relevant.

[5]Note that our objective is to highlight possible mechanisms for the effect rather than to test for which of these accounts is supported by the data.

[6]In reality, the productivity frontier is not guaranteed even when experienced users apply existing technologies. For example, Allen and Lun (2011) document that even experienced teachers do not apply the best teaching practices in secondary school classrooms.

[7]Note that typically, online influencers are compensated for promoting products; in our case there was neither the requirement that they post messages nor an incentive if they did so.

[8]We urge caution while interpreting the results for the CARs since these are not directly observed outcomes generated by the randomization unlike the trial and adoption rates.

[9]We recognize that this analysis has a more causal flavor and note the limitations of an analysis that conditions on trial.

[10]Note that in this particular instance we did not need to pay the influencers. This situation may not carryover to other contexts.

FIGURE 1. EXPERIMENTAL DESIGN

Basic information about
the technology

**Village-level
Intervention**

Communication
Medium

Online
Influencers

Mobile Social Media
Support Platform

Firm initiated
One-on-one Service
and Support

No Intervention

Yes   No
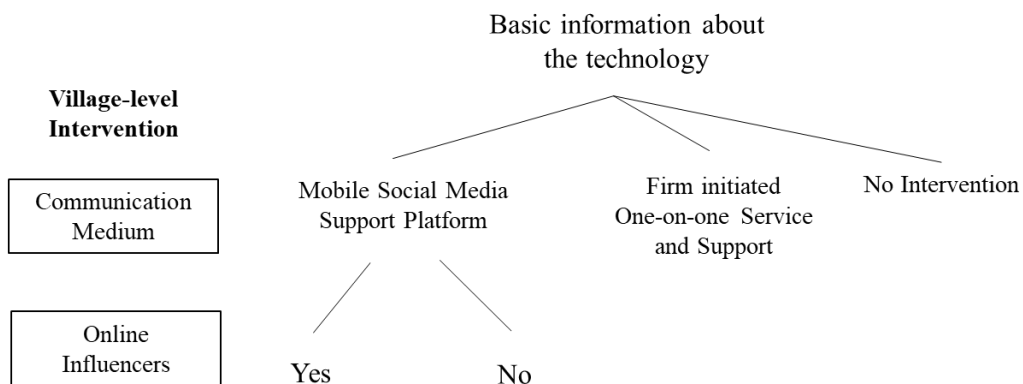
FIGURE 2. INFORMATION SOURCES BY TREATMENTS

Treatment	No. Villages	No. Farmers	Sources of Information				
			Self-Experimentation	Offline Social Interaction	Customized Expert Instruction	Online Social Interaction	Information from Influencers
Control	8	148	Y	Y	N	N	N
Firm's one-on-one Support	8	172	Y	Y	Y	N	N
Social Media	8	121	Y	Y	Y	Y	N
Social Media w Influencers	10	202	Y	Y	Y	Y	Y

FIGURE 3. RESEARCH PROCEDURE

Social media w influencers

Social media

Firm's one-on-one support

Control

Information sessions
• Introduce the new technology
• Conduct a background survey
• Distribute free samples

Application
of the new
technology

Adoption

Timeline

*1st Follow-up
Survey*

*2nd Follow-up
Survey*

*3rd Follow-up
Survey*

Day 1

Week 1 – Week 8
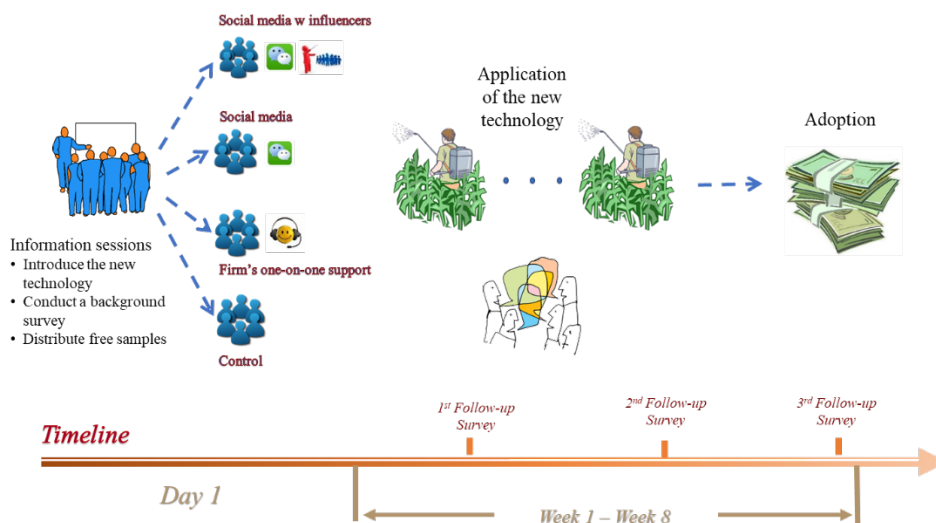
FIGURE 4. CHANGES OF ONLINE SOCIAL INTERACTIONS OVER TIME
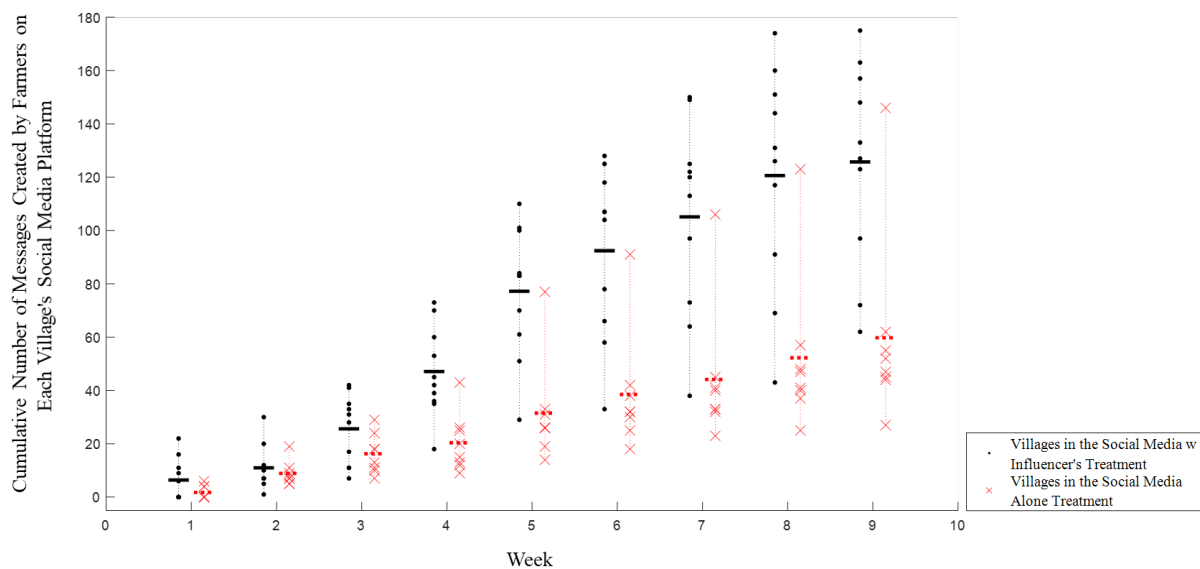
Notes: This figure shows the changes in the cumulative number of messages created by farmers on each village's social media platforms. Villages in the social media with influencers treatment and social media alone treatment are represented by black dots and red crosses respectively. The mean values of social media with influencers treatment are denoted by black bars and social media alone treatment are red dotted bars.

FIGURE 5. CHANGES OF ONLINE SOCIAL INTERACTIONS OVER TIME BY TOPICS
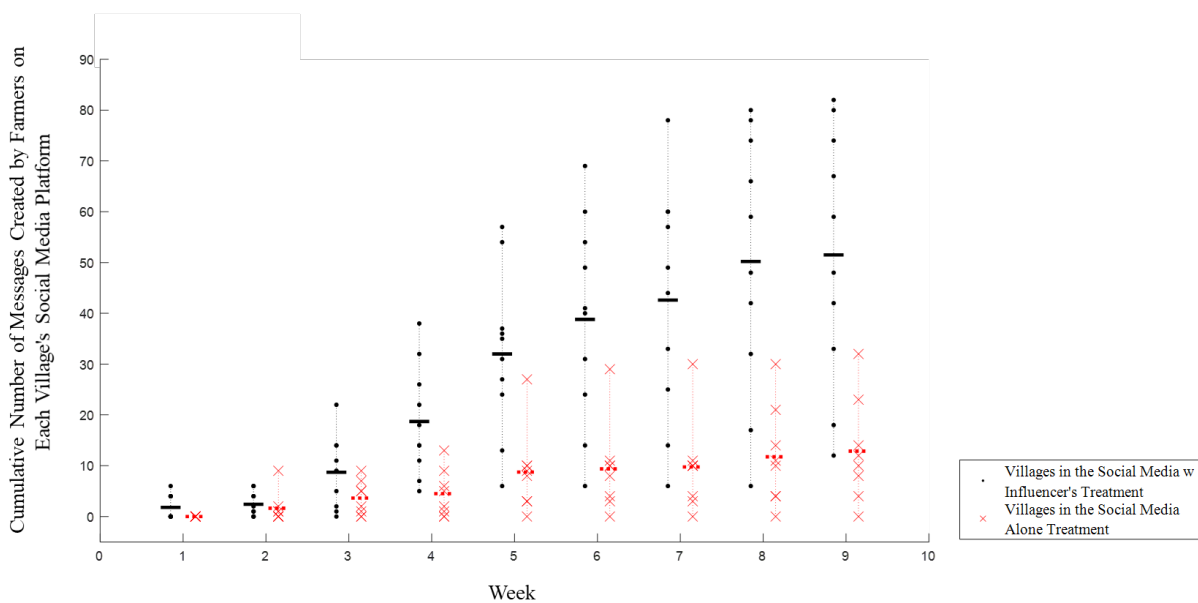
(a) New pesticide and trial program related topics
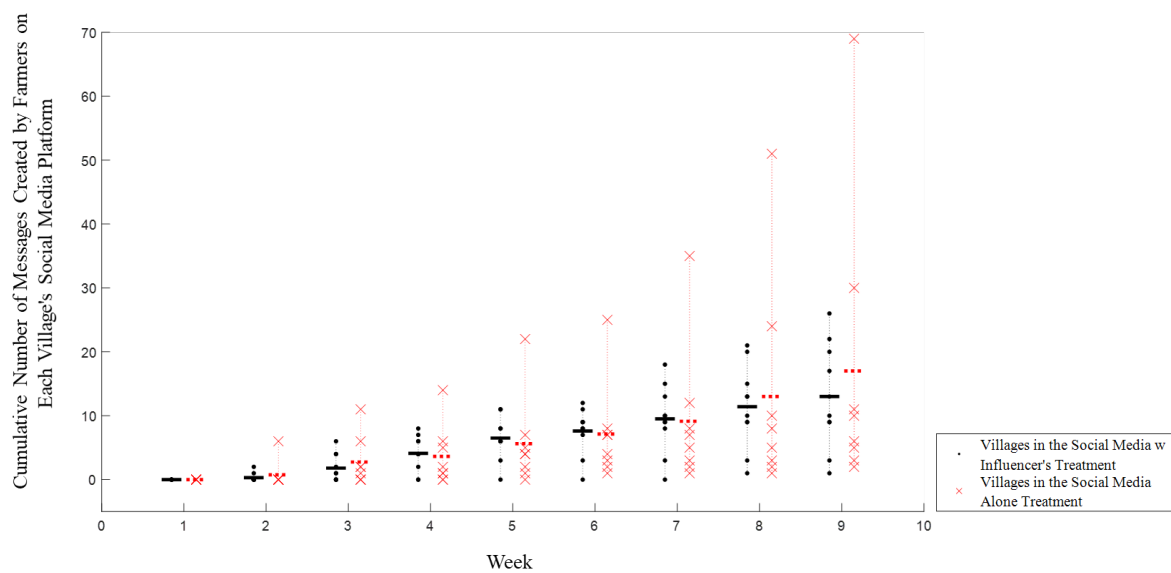
(b) Unrelated topics

Notes: These figures show the changes in the cumulative number of messages created by farmers on each village's social media platforms. Villages in the social media with influencers treatment and social media alone treatment are represented by black dots and red crosses respectively. The mean values of social media with influencers treatment are denoted by black bars and social media alone treatment are red dotted bars. Subfigure (a) contains messages on the new pesticide and trial program related topics, and subfigure (b) contains messages on unrelated topics.

TABLE 1. SUMMARY STATISTICS BY TREATMENT TYPES

Treatment		Social media w influencers	Social media	Firm's one-on-one support	Control	Overall
Observations		202	121	172	148	643
No. Villages	Number	10	8	8	8	34
Village size	Mean	20.20	15.11	21.50	18.50	18.91
	Stdev	7.52	4.12	4.50	3.30	5.59
Gender	Mean	.67	.65	.65	.67	.66
	Stdev	.47	.48	.48	.47	.47
Age	Mean	50.20	48.02	52.39	52.86	50.98
	Stdev	7.77	8.67	8.16	9.09	8.53
Current or previous village official (1 = Yes, 0 = No)	Mean	.22	.18	.17	.18	.19
	Stdev	.41	.39	.38	.38	.39
Education level[a]	Mean	1.24	1.21	1.17	1.18	1.23
	Stdev	.43	.41	.38	.39	0.42
Number of people in the family who farm	Mean	2.17	2.21	2.10	2.02	2.12
	Stdev	.71	.77	.69	.46	.67
Owning arable land larger than 3.3 acres (1 = Yes, 0 = No)	Mean	.42	.37	.39	.37	.39
	Stdev	.49	.49	.49	.48	.49

a. 0 = Primary school and below, 1 = Middle school, 2 = High school, 3 = College and above.

Notes: This table shows various characteristics of the villages in the different groups. It is also indicative of the similarities in the samples in each of the treatment and control conditions.

TABLE 2. SUMMARY STATISTICS FOR TOPICS DISCUSSED IN THE ONLINE CONVERSATIONS

			No. of messages per farmer		
	Online message types	Statistics	Social media w influencers	Social media	Overall
(1)	Farmers show application evidence (photos or videos)	Mean	1.985	0.838	1.476
		StdDev	1.709	1.047	1.530
		Min	.187	0	0
		Max	5.455	2.654	5.455
(2)	Farmers provide descriptions on efficacy of the new pesticide	Mean	.375	.087	.247
		StdDev	.411	.141	.345
		Min	0	0	0
		Max	1.091	0.379	1.091
(3)	Farmers raise questions or provide answers to inquires about the new pesticide	Mean	.812	.440	.647
		StdDev	.877	.559	.756
		Min	0	0	0
		Max	2.382	1.327	2.382
(4)	Farmers raise questions or provide answers to inquires about the trial program	Mean	1.017	.339	.716
		StdDev	.367	.407	.510
		Min	.409	0	0
		Max	1.509	1.124	1.509
(5)	Researchers answer farmers' questions related to the new pesticide	Mean	1.155	.573	.896
		StdDev	1.052	.363	.854
		Min	0	0	0
		Max	3.096	.974	3.096
(6)	Farmers show trial program related photos or videos	Mean	.743	.053	.436
		StdDev	.813	.099	.692
		Min	0	0	0
		Max	2.661	.216	2.661
(7)	Topics unrelated to the new pesticide	Mean	1.305	1.981	1.605
		StdDev	.767	1.373	1.099
		Min	.057	.379	.057
		Max	2.851	3.796	3.796

Notes: We classified the various conversations into 7 main topic areas. This table describes each of these topics and also provides descriptive statistics regarding each one.

TABLE 3. EFFECTS OF MARKETING TREATMENTS ON TRIAL AND ADOPTION BEHAVIORS
(GROUP-LEVEL ANALYSIS)

(a) Estimation results (OLS)

DVs	Early trial Rate	Final trial Rate	Adopt. rate	Cond. adopt. rate
Social media w influencers	.251***	0.220***	0.338***	0.268***
	(.069)	(.044)	(.074)	(.083)
Social media	-.076	-.055	.178***	.327***
	(.071)	(.068)	(.048)	(.069)
Firm's one-on-one support	.010	.188***	.307***	.265***
	(.057)	(.059)	(.046)	(.055)
Constant	.391***	.666***	.244***	.380***
	(.042)	(.034)	(.032)	(.054)
Observations	34	34	34	34
R-squared	.476	.506	.503	.449
Village-level clustered errors	YES	YES	YES	YES
(b) Across-treatment coefficient difference tests (Wald and Wild cluster bootstrap-t test)				
Social media w influencers = Social media	17.61 ***	17.75***	4.36**	.58
Social media w influencers = Firm's one-on-one support	13.32 ***	.33	.17	0
Social media = Firm's one-on-one support	1.61	1.15***	6.84**	1.81

*** p<.01, ** p<.05, * p<.1.

Notes: This table provides regression results for each of our outcome measures as dependent variables regressed on the treatment dummies. Constant represents the value for the Control group. Robust standard errors are in parentheses.

TABLE 4. EFFECTS OF MARKETING TREATMENTS AND CONTROL VARIABLES ON
ADOPTION BEHAVIOR (INDIVIDUAL-LEVEL ANALYSIS)

IVs[a]	(1)	(2)	(3)
Social media w influencers	1.805***	1.742***	1.386
	(.397)	(.395)	(3.143)
Social media	1.217***	1.291***	1.968
	(.295)	(.314)	(3.344)
Firm's one-on-one support	1.706***	1.736***	-3.298
	(.296)	(.280)	(3.220)
(Social media w influencers)*Age			.003
			(.039)
Social media *Age			.053
			(.035)
Firm's one-on-one support *Age			.080**
			(.033)
(Social media w influencers)* Most important pesticide purchase determinant: price			-.982**
			(.486)
Social media*Most important pesticide purchase determinant: price			-1.438**
			(.684)
Firm's one-on-one support *Most important pesticide purchase determinant: price			-.736
			(.466)
(Social media w influencers)* Most important pesticide purchase determinant: health hazard			13.256***
			(1.016)
Social media* Most important pesticide purchase determinant: health hazard			14.972***
			(1.254)
Firm's one-on-one support * Most important pesticide purchase determinant: health hazard			12.747***
			(1.201)
Gender		.098	.957*
		(.223)	(.524)
Age		-.009	-.051**
		(.013)	(.026)
Current or previous village official		.406	.452
		(.247)	(.592)
Education level		-.061	.035
		(.167)	(.257)
Number of family members who farm		-.109	-.316
		(.170)	(.760)
Owning arable land larger than 3.3 acres		.333*	-.257
		(.191)	(.520)
Had monetary loss due to pests in previous two years		.041	.090
		(.239)	(.729)
Thinks there is a chemical residue problem in the land		.179	.146
		(.246)	(.756)
Most important usage amount determinant: self-usage experience and manual		-.017	.002
		(.179)	(.288)
Most important usage amount determinant: recommendations from friends		-.218	.411
		(.334)	(1.041)
Has attended agricultural training before		-.058	.331
		(.223)	(.771)
Knows the name or ingredients of pesticides		-.219	-.258
		(.204)	(.265)
Has positive evaluation on extant pesticide brands		.127	-.008
		(.212)	(.195)
Most important pesticide purchase determinant: price[b]		.145	.930***
		(.182)	(.359)
Most important pesticide purchase determinant: health hazard		-.284	-13.092***
		(.337)	(.763)
Constant	-1.423***	-1.011	.646
	(.270)	(.885)	(2.855)
Observations	467	467	467
Village-level clustered error	YES	YES	YES
AIC	605.49	625.52	618.23
BIC	622.08	704.30	771.64

a. To save space, we do not display insignificant interaction terms.
b. The baseline of the most important purchase factor is product effectiveness.
*** $p<.01$, ** $p<.05$, * $p<.1$.
Notes: This table provides logit model results estimated using farmer-level data for the effects of the treatments and other controls on the various outcomes of interest. Robust standard errors are in parentheses.

TABLE 5: DESCRIPTIVE STATISTICS OF MESSAGES POSTED BY NON-INFLUENCER FARMERS ON SOCIAL MEDIA

			Related topics		Unrelated topics
Treatment	Stats		Product effect.[a]	All others[b]	Unrelated topics
First Two Weeks	Social media w influencers	Mean	1.70	.70	.30
		Std	2.21	.82	.67
		Min	.00	.00	.00
		Max	5.00	2.00	2.00
	Social media	Mean	.50	1.13	.75
		Std	.76	2.80	2.12
		Min	.00	.00	.00
		Max	2.00	8.00	6.00
Third to Eighth Week	Social media w influencers	Mean	9.60	38.20	11.10
		Std	8.80	22.59	6.42
		Min	.00	4.00	1.00
		Max	29.00	74.00	2.00
	Social media	Mean	3.50	6.63	12.25
		Std	4.72	6.72	17.30
		Min	.00	.00	1.00
		Max	12.00	18.00	51.00

a. Product effectiveness and usage related messages posted by farmers.
b. All the other new pesticide and trial program related messages, such as sending application photos.
Notes: This table shows the number of product-related and other messages posted by the farmers on social media in the first two weeks and subsequent weeks of the intervention. We exclude messages from the eminent village personality influencers in constructing the table.

TABLE 6: FARMERS' BELIEFS ON SUPERIORITY OF THE NEW PESTICIDE COMPARED TO TRADITIONAL PESTICIDES ALONG FOUR ATTRIBUTES: EVIDENCE OF LEARNING

Treatment	Effectiveness		Harm to crops		Usage reduction		Program usefulness	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Social media w influencers	.470	.500	.228	.420	.431	.496	.698	.460
Social media	.355	.481	.182	.387	.273	.447	.595	.493
Firm's one-on-one support	.523	.501	.477	.501	.552	.499	.605	.490
Control	.284	.452	.209	.408	.236	.426	.372	.485
Total	.420	.494	.281	.450	.389	.488	.579	.494
Across-treatment difference tests								
Social media w influencers = Social media	**		-		***		*	
Social media w influencers = Firm's one-on-one support	-		***		**		*	
Social media = Firm's one-on-one support	***		***		***		-	
Social media w influencers = Control	***		-		***		***	
Social media = Control	-		-		-		***	
Firm's one-on-one support = Control	***		***		***		***	

*** $p<.01$, ** $p<.05$, * $p<.1$

Notes: This table reports farmers' responses regarding various attributes of the pesticides and their agreement with whether the new pesticide is superior on these attributes. Numbers represent the proportions agreeing or strongly agreeing to the new pesticide's superiority.

TABLE 7: EFFECTS OF MARKETING TREATMENTS ON FARMERS' BELIEFS
ABOUT THE NEW PESTICIDE (INDIVIDUAL-LEVEL ORDERED LOGIT)

DV	(1) Effectiveness	(2) Harm to crops	(3) Usage reduction
Social media w influencers	.680**	.133	.775**
	(.338)	(.441)	(.309)
Social media	.775***	.161	.664**
	(.264)	(.479)	(.301)
Firm's one-on-one support	.668**	1.464***	1.207***
	(.282)	(.428)	(.294)
Gender	.006	.000	.212
	(.164)	(.237)	(.192)
Age	-.012	.014	-.010
	(.010)	(.013)	(.010)
Current or previous village official	.598***	.093	.439*
	(.212)	(.271)	(.251)
Education level	-.110	.246	-.014
	(.157)	(.169)	(.128)
Number of family members who farm	-.249***	-.068	-.120
	(.083)	(.136)	(.125)
Owning arable land larger than 3.3 acres	-.016	-.230	-.126
	(.201)	(.223)	(.164)
Observations	494	494	494
Village-level clustered error	YES	YES	YES
AIC	1299.57	813.03	123.55
BIC	1354.20	867.66	1285.18

*** p<.01, ** p<.05, * p<.1.

Notes: This table presents results from an ordered logit analysis with farmer-level data where the dependent measure is the agreement on a 5-point scale with whether the new pesticide is superior to existing pesticides along the three attributes of interest. Robust standard errors are in parentheses.