THE EFFECT OF FIRM MARKETING CONTENT ON PRODUCT SALES: EVIDENCE FROM A MOBILE SOCIAL MEDIA PLATFORM

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ABSTRACT

Despite the extensive use of marketer generated content (MGC) as a dominating social media marketing tool, marketers haven't reached a clear understanding about whether MGC has impact on sales and what type of content is effective. In this study, we quantify the impact of social media MGC on product sales and specifically examine the effect of different types of contents, i.e., informative content, persuasive content, and promotional content. Based on a quasi-experiment design, we apply difference-in-differences method on a unique data set with firm MGC activities on a mobile social media platform and the corresponding product sales. We find that MGC has positive and significant effect on product sales. The overall sales elasticity is 51.47%, which means an average 51.47% increase of product sales after MGC marketing. Furthermore, we find that marketing content is a key in generating sales. In general, informative social media marketing content is more effective in stimulating product sales than persuasive and promotional contents. However, such content effect is subject to product categories. Specifically, for sales of high-involvement products, informative content is more effective, whereas persuasive content and promotional content are more sales effective for low-involvement products. Marketers may develop appropriate social media strategy and design marketing contents accordingly.

Keywords: Social media marketing; Marketer generated content; Content analysis; Product involvement; Difference-in-differences

1. Introduction

Social media has been popular over the past few years among both individual users and firms, due to its nature of social interaction. It attracts individual users by having many functions and benefits such as making new friends, sharing opinions, and interacting with other people. For firms, social media gives a unique opportunity to reach potential consumers more easily and more targeted. Thus, firms are continuously using social media to market their brands and products, and interact with consumers. Marketer generated content (MGC) has become a dominating firm social media marketing activity. On social media platform, especially on mobile social media platform, content distribution is much faster and wider. Despite the extensive use of social media, however, firms have not reached a clear understanding of whether and how much MGC affects firm marketing performance.

Due to the lack of performance evaluation, firms are indecisive about their social media marketing efforts. Some are skeptical about MGC effect. For example, General Motors, the famous automaker, said that their marketing efforts on Facebook were ineffective, and therefore discontinued its Facebook advertising campaigns [The Huffington Post 2012]. Meanwhile, some firms are advocates and capable of using social media. Dell is a successful case. During the year 2007 to 2009, Dell had kept posting MGC on Twitter to notify its consumer exclusive deals, which directly brought three million dollars' revenue. These two different cases suggest that it is critical for marketers to evaluate their social media efforts, as effects of social media marketing can be different for firms selling different kinds of products.

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When designing social media marketing, appropriate content makes difference because it affects how embedded information is perceived by consumers. In practice, marketers usually employ both informative content and persuasive content. Informative content is the most common type of content that marketers employ on social media platforms. It provides product and brand information for consumers and enables consumer interactions and engagement [Gaber & Wright 2014]. Persuasive content, on the other hand, is more effective in attracting consumers' attention, keeping them on the page, and convincing them toward final purchase [Muhammad et al. 2014]. However, in prior literature, it lacks specific examination on the sales effect of different types of social media marketing contents. Having this knowledge could help firms improve their social media marketing performance.

Motivated by the above considerations, we aim to address the following issues in this study. First, we examine the sales effect of firm social media marketing at the product-level and for various firms. Prior literature on the effect of social media marketing solely focuses on single firm at the individual (consumers of the firm) level such as Goh et al. [2013] and Rishika et al. [2013]. By looking at multiple firms selling different kinds of products, we believe findings from our study are more generalized. Second, while existing literature on the effect of social media MGC mainly focuses on metrics of MGC such as volume and valence, we add new evidence by looking at how content types may affect corresponding product sales. In the literature, the only exceptions that have explored MGC contents are Goh et al. [2013], Tucker [2014], and Lee et al. [2016]. However, they have inconsistent findings. Goh et al. [2013] and Lee et al. [2016], by classifying MGC into informative content and persuasive content, found that the sales effect of social media marketing is through persuasive communications, whereas findings from Tucker [2014] concluded that the viral advertisement content is generally less persuasive. Third, we examine how the sales effect of MGC contents varies with product categories that has not been studied in existing literature.

Overall, our research questions are: Whether social media MGC has impact on product sales? If so, what type of marketing content is more sales effective? And whether such content effect varies with product categories? The launch (in Nov. 2013) of store-oriented microblogging services, i.e., WeiTao, on Taobao mobile platform provides us a unique opportunity to answer these research questions.[1] It joints firm social media marketing contents (i.e., store microblogs) with product sales. Taobao stores can create their brand communities and post contents (i.e., MGC) on WeiTao platform. Such contents include product and brand information and sales promotion. Consumers may find the information useful and follow store WeiTao to receive more contents.

The launch of WeiTao enables us a quasi-experiment to quantify the impact of social media marketing on product sales. To understand the effect of different types of social media contents, we, following literature, code WeiTao contents as informative, persuasive, and promotional. Empirical results show that, overall, social media marketing has positive and significant impact on product sales — the average sales increase after WeiTao marketing is 51.47% (for a ±4 days time window). Meanwhile, informative content is in general more effective in product sales than persuasive and promotional contents. We further examine whether such content effect varies with product categories, and find that informative content is more sales effective for high-involvement products, whereas persuasive content and promotional content are more effective for the sales of low-involvement products. Our results hold for various robustness checks.

This study has potential to contribute to social media marketing and advertising content literature. First, it quantifies the economic impact of firm social media marketing at the product-level, contributing to the literature of ROI of social media marketing. Our results encourage firms to continue this proactive way of consumer interaction — social media marketing; second, it explores the role of marketing content types in affecting product sales and finds that informative content is more effective in general. Understand this could help firms create appropriate contents when conducting social media marketing; third, it further finds that different types of marketing contents might be suitable for different kinds of products. Firms, therefore, need to consider their product nature to design proper marketing contents.

The rest of this paper is structured as follows: in Section 2, we briefly review the literature that is relevant to our study. Section 3 describes our model specifications and data. Our empirical results are presented in Section 4, and Section 5 summarizes this work and discusses theoretical and managerial implications, as well as limitations.

2. Literature Review

In this section, we briefly describe streams of literature that inform our study: marketer generated content, advertisement content, and product involvement research. Our study is at the confluence of these streams of work, as discussed below.

2.1. Marketer Generated Content

[1] Taobao (www.taobao.com) is the largest e-commerce platform in China.

Marketer generated content (MGC) is marketer initiated marketing communications [Kumar et al. 2016]. It is provided for consumers to share with others about a product or service [Godes & Mayzlin 2009]. MGC, as the only authoritative information source, could inform consumers of products and drive sales [Cole et al. 2012]. It is complementary to user generated content when consumers make purchase decisions [Bronner & De Hoog 2010; Qi et al. 2014]. Consumers search both marketer generated content and user generated content to make informed choices.

With the development of social media, MGC is increasingly popular on social media platforms [Libai et al. 2010]. Firms could proactively engage in social media activities and create emotional connections with consumers with the aid of MGC [De Vries et al. 2012]. It helps firm develop one-to-one or one-to-many relationships with consumers due to the interactive nature of social media [Kumar et al. 2016]. Consumers could interact with the marketer by retweeting, commenting, and liking MGC that would bring positive attitude toward products and brands.

Studies have examined the effect of MGC valence and receptivity on sales [e.g. Goh et al. 2013; Kumar et al. 2016]. The valence of MGC reflects sentiment, which is usually classified into three categories, i.e. positive, neutral, and negative. The receptivity of MGC is a unique measure under social media context, which refers to the interactions between marketers and consumers. It is an integration of liking, commenting, and retweeting [Kumar et al. 2016]. Researchers have found that both valence and receptivity of MGC have significantly positive effect on sales, with the effect of MGC receptivity being stronger.

However, few studies explored the effect of content itself except Goh et al. [2013] and Lee et al. [2016], which have not reached consistent conclusion on how MGC content influences sales. Lee et al. [2016] found that informative content of MGC has positive effect on consumer engagement, whereas Goh et al. [2013] found that information richness of MGC has no significant effect on sales. Besides, the classification framework for informative and persuasive contents in these studies is inconsistent. Most of them followed the classification framework for informative content defined in advertising content literature [see e.g., Lee et al. 2016], however, the framework for persuasive content is rather diverse. Goh et al. [2013] treated MGC valence as persuasive effect, while Lee et al. [2016] followed the classification framework proposed in advertising content literature to define persuasiveness. We, therefore, discuss advertising content literature in the following to inform the content classification framework in our study.

2.2. Advertising Content

Marketer generated content on social media platform is similar to advertising on traditional media such as television [Kumar et al. 2016]. Advertising is an input for the consumers. Advertising contents are important component of this input and form the advertising strategy that triggers consumer behavior and firm performance [Vakratsas & Ambler 1999]. Advertising contents are evaluative and serve as a useful tool to persuade consumers [Goh et al. 2011]. It drives consumers' behavioral responses (e.g. website visit intention), which lead to purchase intention [Martínez-Navarro & Bigné 2017]. Here we borrow the perspective of advertising content on traditional media to study the sales effect of social media MGC content.

Prior literature classifies advertising content as informative or persuasive [e.g., Abernethy & Franke 1996; Bertrand et al. 2010; Goh et al. 2013; Liaukonyte et al. 2015]. Informative content refers to factual data on the nature and functions of products or services that could reduce uncertainty [Abernethy & Franke 1996], whereas persuasive content is a concept that assumes consumers already have an understanding of the nature and functions of product but need to be convinced for the benefits of the product that distinguish it from alternatives in the market [Armstrong et al. 2010; Berger & Milkman 2012; Nan & Faber 2004].

Emerging literature in advertising starts to investigate the content effect on sales. This stream of literature mainly focuses on the advertisement on traditional media platforms, such as magazines [Berger & Milkman 2012], and television [Anand & Shachar 2011; Liaukonyte et al. 2015]. They find that informative advertising content could inform consumers of observable product attributes [Resnik & Stern 1977], match consumers with products [Anand & Shachar 2011], and increase purchases, thus have a positive net effect on sales [Liaukonyte et al. 2015]. Persuasive content such as emotional content could arouse consumers' emotions, drive social transmission [Berger & Milkman 2012], and thus increase sales [Liaukonyte et al. 2015].

Most of the research about advertising content on traditional media platforms found that persuasive content is more sales effective than informative content [e.g. Christensen et al. 1997; Holmes & Desselle 2004]. However, there is no consistent conclusion about the effect of content types on new media platforms such as social media platform, in both theory and practice. Goh et al. [2013] and Lee et al. [2016] found the effect of social media marketing on sales is through persuasive communications, whereas findings from Tucker [2014] concluded that the viral advertisement content is generally less persuasive.

Based on the status quo of this stream of literature, we aim to examine the sales effect of different types of contents on social media platform in this study. We follow the information categories proposed by Resnik & Stern [1977] to measure the informative content of MGC. In our research context (as described in details in Section 3), any productpertinent facts, such as product functions, product quality, and product origins, are classified as informative content. As for persuasive content, we refer to the framework proposed by Lee et al. [2016] to determine whether contents are generated to persuade consumers and promote firm-consumer relationship. Our classification framework is listed in Table 1.

2.3. Product Involvement

Though prior studies have examined the effect of content types on sales, there is a lack of research on how the effect varies with product categories as the effect can be different for different kinds of products. In this study, we examine the moderating role of product categories (taking product involvement perspective) on the effect of content types. We, here, discuss related literature of product involvement and our underlying reasoning.

Product involvement is an important attribute of product, which denotes a consumer's enduring perceptions of the importance of product category based on the consumer's inherent needs, value, and interests [Muncy & Hunt 1984; Zaichkowsky 1985]. Taking consumers as a group, products differ in their tendency to raise involvement. Low-involvement products refer to products, which most consumers perceive little linkage to their important values, and product class where there is little commitment to the brands; whereas high-involvement products refer to products that carry a high value or high level of purchase risk for consumers [Lastovicka 1979]. Usually, low-involvement products have a low risk of purchase failure or have a low price tag, while high-involvement products have a high risk of purchase failure or high price tag for consumers [Assael 1984].

Studies have shown that product involvement influences consumers' decision-making processes, the extent to which consumers will search for product information, their perceptions of alternatives in the same product category, and their brand loyalty [Bian & Moutinho 2009; Liao et al. 2016; Quester & Lin 2003; Zaichkowsky 1985]. Consumers typically go through different decision-making processes based on product involvement [Assael 1984; Engel et al. 1995]. For instance, it involves more information searching for consumers to buy high-involvement products due to the product nature of high value or high risk [Zaichkowsky 1985].

In line with product involvement, Pretty and Cacioppo [Pretty & Cacioppo 1986] developed the Elaboration Likelihood Model, which established the foundation for understanding the elaboration process of advertising content. According to them, the elaboration process of advertising content goes through two different routes, i.e. central route and peripheral route. When buying a high-involvement product, consumers have high level of ability and motivation to process information through the central route. They feel more relevant to advertising content and put more efforts in processing content information. Consumers can be persuaded by the information related to product features in the advertisement that enhances their intention to purchase [Te'Eni-Harari et al. 2009]. Under low product involvement situation, consumers elaborate marketing content via the peripheral route and focus on peripheral information such as brand or attractive characters appearing in the advertisement.

To determine the level of product involvement for a given product category, researchers have developed scales to measure product involvement [Bloch 1981; Zaichkowsky 1985]. For instance, Zaichkowsky [1985] developed a measurement scale called PII (Personal Involvement Inventory). Based on PII, cosmetics products were defined as high-involvement products [Brisoux & Cheron 1990], and stationery goods such as pens were established as low-involvement products [Mittal 1989].

In our study, we examine whether the effect of social media marketing and the effect of marketing content types vary with product categories. We take the product involvement perspective and follow the literature to study cosmetics as high-involvement products since cosmetics products directly affect consumers' self-images and have many features making it risky to buy a satisfactory one [Park & Moon 2003; Suh & Youjae 2006]. We study stationery goods as low-involvement products as they are low-valued consumables [Martin 1998].

3. Model Specifications and Data

Our data in this study is crawled from Taobao (www.taobao.com), which is the largest e-commerce platform in China. In Nov. 2013, Taobao launched a store-oriented microblogging service called WeiTao on its mobile platform. It becomes the key marketing tool for Taobao stores. Stores can create brand communities on WeiTao to market their products. They generate contents to engage with consumers. Consumers can follow the stores they like and receive product and store information. The launch of WeiTao enables us a quasi-experiment to examine the effect of store MGC. Therefore, we use difference-in-differences (DID) method to quantify this main effect. Specifically, since the marketer generated contents contain product marketing information, we conduct this study at the product-level, that is, examining pre- and post-WeiTao sales difference between WeiTao-marketed products and non-WeiTao-marketed products. Then, we analyze what type of contents is more sales effective by examining WeiTao product-marketing contents and the corresponding product sales.

3.1. Model Specifications

We conduct DID at the product-level to examine the effect of social media MGC on product sales. The corresponding model is presented in Equation (1) and we use expectation-maximization (EM) to estimate it.

$$\ln sales_{ijt} = \alpha_0 + \alpha_1 Treat_i + \alpha_2 After_{it} + \alpha_3 Treat_i \times After_{it} + \Theta X_i + u_j + \varepsilon_{ijt},$$
$$u_j = u_{0j} + u_{1j} \ln credits_j . \tag{1}$$

In Equation (1), i denotes a product of experiment group or control group (see Section 3.2 for details of how we formed our experiment and control groups), j denotes store j that product i belongs to, and t denotes time period (we take four days before and four days after WeiTao marketing the product i).[2] The experiment group includes all products that are marketed by WeiTao microblogs. For each product in the experiment group, it is matched with a control product that is sold by the same store and very similar to the experiment product, but the control product has never been marketed on WeiTao. The dependent variable $sales_{ijt}$ denotes product sales (in quantity) four days before and four days after the marketing of the experiment product on WeiTao. It is worth to note that although the overall store-level impact of WeiTao can be long-run, we think the influence of specific WeiTao contents on product sales is shorter due to the timeliness of WeiTao microblogs. Therefore, we take four days before and after WeiTao marketing as our time window to measure the effect on product sales.

Key independent variables in Equation (1) include: $Treat_i$, a dummy variable that equals 1 if the product is marketed by WeiTao and 0 if not; $After_{it}$, a dummy variable that equals 1 for period after WeiTao marketing and 0 for before; the interaction term $Treat_i \times After_{it}$ shows the effect of social media MGC on product sales, and its coefficient α_3 is our focus. We also include a variety of variables X_i in Equation (1) to control store and product characteristics, including logarithm of store opening WeiTao date (ln*opentime*), product price (ln*price*), the number of product colors or options (*color*), shipping fee (*delivery*), the number of comments the product received (ln*comments*), and the number of consumers who bookmarked this product (ln*collection*).

Product sales vary from store to store due to store-level heterogeneity. Since our focus is at the product-level, we treat our sample stores as a random sample from a larger population and model the between-store variability. To do so, we add random effect u_j in our main model to control store-level heterogeneity. The between-store variability is highly correlated with store size and we use accumulated store credits since store opening date ($\ln credits_j$) to proxy store size.[3] This gives us a multi-level analysis as shown in Equation (1) and we use EM to ensure asymptotic unbiased estimation.

Based on the main effect of social media MGC, we further examine what type of marketing contents is more sales effective. We conduct hierarchical regression for the following models, i.e., Equation (2) and Equation (3), on the sample of experiment products.

$$\ln sales_{ijt} = \beta_0 + \beta_1 After_{it} + \Omega X_i + v_j + \xi_{ijt}, \tag{2}$$

$$\begin{aligned}\ln sales_{ijt} = {} & \gamma_0 + \gamma_1 After_{it} + \gamma_2 After_{it} \times Informative_{it} + \gamma_3 After_{it} \times Persuasive_{it} + \gamma_4 After_{it} \times Promotional_{it} \\ & + \gamma_5 After_{it} \times \ln WordNum_{it} + \Pi X_i + w_j + \mu_{ijt}.\end{aligned} \tag{3}$$

Equation (2) and Equation (3) examine the effect of WeiTao marketing and marketing contents on product sales for the experiment group. The dependent variable in both equations is $sales_{ijt}$, which is the product sales four days before and four days after the product WeiTao marketing. The key independent variable in Equation (2) is the same dummy variable $After_{it}$ as in Equation (1). If its coefficient, β_1, is positive and significant, we can conclude that social media MGC is sales effective for experiment group. For Equation (3), we add WeiTao content types, which are $Informative_{it}$, $Persuasive_{it}$, and $Promotional_{it}$, into the model to examine which type of WeiTao contents is significant in influencing product sales. Besides, we include $WordNum_{it}$, which is the length of WeiTao microblog in terms of the number of words, into our model as a control variable. The interaction terms $After_{it} \times Informative_{it}$, $After_{it} \times Persuasive_{it}$, and $After_{it} \times Promotional_{it}$ yield the effects of WeiTao content types on product sales, and their coefficients γ_2, γ_3, and γ_4 are our focus. All other store and product information, X_i, are the same as in Equation (1) as control variables. Store-level heterogeneity, v_j and w_j, are also the same as u_j in Equation (1).

3.2. Data Collection

We collect all Taobao stores that opened WeiTao for MGC marketing, extract their WeiTao contents for product marketing, and obtain corresponding product sales. To examine the effect of product involvement, we focus on stores selling cosmetics products as our high-involvement sample and stores selling stationery products as the low-

[2] We also conduct DID analysis with ±2 days and ±3 days time windows for sake of robustness. Results are consistent and provided in Section 4.3.

[3] On Taobao, every transaction accumulates the store a credit of 1, 0, or -1 depending on the consumer gives a positive, neutral, or negative review, respectively.

involvement sample (as discussed in Section 2.3). The data collection process is as follows: first, we searched keywords "cosmetics" and "stationery" on WeiTao mobile search page and obtained WeiTao store list. We dropped Tmall WeiTao accounts from our list and only kept Taobao WeiTao accounts, to avoid systematic difference between Taobao (C2C) stores and Tmall (B2C) stores.[4] Second, based on the WeiTao store list from the first step, we retrieved each WeiTao account's opening date, all posted microblogs, and corresponding store webpage. Third, we took time period of Aug. 15, 2014 to Oct. 31, 2014, in which WeiTao marketing became active, to examine all WeiTao microblogs published in that period by the stores in our WeiTao list. When a microblog contains product marketing content, it usually includes the product's URL page. We therefore obtained a list of all products marketed in WeiTao microblogs and their corresponding Taobao product pages. Note that we kept products that were only marketed once to avoid systematic bias among products. These products make up our experiment group. Finally, based on the product URL page, we crawled product information including product price, colors or other options, shipping fee, the number of comments this product received, the number of consumers who bookmarked this product, and its sales transaction history in past 30 days. Based on the store webpage, we obtained store information such as accumulated store credits.

Since the marketed products (i.e., our experiment group) are chosen by the sellers, we need a control group to deal with the selection bias issue. We used the "consumers who viewed this item also viewed" function in the experiment product page to choose the control product.[5] In each experiment product page, the "consumers who viewed this item also viewed" function recommends four to six products that are very similar to the experiment product, according to consumers' browsing history. Recommended products not only belong to the same product sub-category as the experimental product but also are similar in various aspects such as product functions, styles, prices, and so on. In another word, these recommended products and the experiment product are substitutes and sold by the same store. Among the recommended products, we chose the one whose price is the closest to the experiment product's as our control product. Note that the control product should have never been marketed on WeiTao. We then obtained store information and product information including product sales transactions of the control group the same way as we did for the experiment group.

Our final sample has 526 products (391 cosmetics and 135 stationery) in the experiment group and 526 products in the control group, altogether from 123 Taobao stores. For each pair of experiment product and control product, we conduct manual check making sure they are substitutes for each other. We also perform group t-tests and find that there is no significant difference in various product characteristics between the experiment group and the control group before WeiTao marketing.

3.3. Content Coding Process

Based on collected WeiTao microblogs, we followed the content classification procedure to classify the contents [Lai & To 2015]. Two independent judges went through training, practice, and then coded the final sample of our WeiTao microblogs. At the training stage, we first explained the content analysis method to the judges. And then, we started with eighteen content attributes, which are defined in prior literature [Abernethy & Franke 1996; Lee et al. 2016] to classify informative content and persuasive content. Informative content includes all factual data of the nature and functions of the product or service, such as product origins, product quality, and functions that could reduce purchase uncertainty [Abernethy & Franke 1996]. Persuasive content refers to contents that convince consumers of benefits of that particular product such as some living tips [Lee et al. 2016]. We collected 100 WeiTao microblogs (containing these attributes) from stores of our WeiTao list. These microblogs were posted before our final sample period. We selected 10 of them to show as examples of attributes to the judges. For the rest 90, we conducted two trainings (45 microblogs each). During each training, we asked the judges to read every microblog and answer whether each microblog has the eighteen attributes, which is a Yes or No for each of the eighteen attributes. We particularly trained the judges to code contents in pictures. Pictures in WeiTao microblogs often contain important information such as product price, functions, and user experience. Usually, product price and user experience are shown in corners of pictures, and product origins and functions are shown on product packaging in the picture. Therefore, judges are trained to pay special attention to these places of each picture. Overall, each training lasted about three hours, and the two judges coded independently without communications during the process. After the trainings, we answered questions from the judges about the coding process.

[4] Tmall is the B2C e-commerce platform embedded in Taobao.

[5] The research setting here restrains us from using more rigorous matching methods such as propensity score matching (PSM) because our experiment products are from many different stores. Since products of different stores are very different, we need the control product from the same store of the experiment product so that they can be similar. Therefore, we cannot generate a pool of control products to match the experiment products from different stores using PSM. Based on this consideration, we used the "consumers who viewed this item also viewed" function provided by Taobao.

After the training, it went to the practice stage. At the practice stage, we collected 61 WeiTao microblogs posted between Aug. 1, 2014 and Aug. 14, 2014 by stores in our list. Note that this practice set is different from both the training set and our final sample. The judges first did a pretest by coding 31 WeiTao microblogs out of the practice set.[6] After that, coding disagreement was discussed until a consensus was reached. Then the judges practiced on the rest 30 WeiTao microblogs. This time, inter-judge percent agreement reached 97%, which is a satisfying reliability level [Lacy & Riffe 1996].[7]

Finally, we proceeded to the final sample coding process. Again, the judges coded the contents with no communications, but they could refer to examples we supplied at the training stage. All WeiTao microblogs in our sample were coded by these two judges. Overall, the inter-judge percent agreement for our final sample was 96%, and the Cohen's Kappa, which is a more robust measure of inter-judge reliability [Lacy & Riffe 1996], was 0.90.

After content coding, we have values of the eighteen attributes for each WeiTao microblog. We then conducted factor analysis with varimax rotation to examine whether our classification of two types of contents with eighteen attributes is proper. In fact, results from scree plot and eigenvalues revealed three factors and ten attributes. We therefore dropped eight insignificant attributes and named the three factors according to their corresponding attributes. The three factors correspond to three types of contents, i.e., informative, persuasive, and promotional. Promotional content involves product price, deal information, and free-shipping information. We therefore distinguish promotional content from the literature-suggested informative and persuasive contents in this study. From our observation, promotional content is an often used type of content in MGC marketing practice in China, especially in the e-commerce context. Overall, for each WeiTao microblog, we get its factor scores on each of the three factors and use the factor scores in our model to examine the effect of MGC contents on product sales.

Table 1 lists our final ten attributes, their classifications, descriptions, and summary statistics. As can be seen, informative content has four attributes *origins*, *productknowledge*, *userexp*, and *quality*, which enable us to assess the informativeness of the content. Three attribute variables *text*, *correlation*, and *lifeknowledge* are persuasive. They show if there is non-descriptive product information in the content and that fits the product. Three variables *deal*, *freeshipping*, and *price* are promotional. Their definitions provide information about product price and promotions. The promotional content is different from informative content in that it emphasizes sales promotions or coupons whereas informative content focuses on product information. Overall, we use these three content types, i.e., informative content, persuasive content, and promotional content, to investigate the effect of social media marketing content on product sales. Meanwhile, we provide descriptions, measurements, and descriptive statistics of all variables of our models in Table 2.

Table 1: Content-Coded Attributes and Their Classifications, Descriptions, and Summary Statistics

Factors	Attributes	Description	Mean	SD	Min	Max
Informative Content	*origins*	Whether there is description of product origins	0.200	0.401	0	1
	productknowledge	Whether there is detailed description of products	0.476	0.501	0	1
	userexp	Whether it mentions user experience	0.171	0.377	0	1
	quality	Whether it mentions product quality	0.206	0.406	0	1
Persuasive Content	*text*	Whether there is a supplementary description	0.624	0.486	0	1
	correlation	Whether the description fits this product	0.547	0.499	0	1
	lifeknowledge	Whether there are living tips	0.276	0.449	0	1
Promotional Content	*deal*	Whether it mentions promotion information	0.394	0.490	0	1
	freeshipping	Whether it mentions that this product is free shipping	0.253	0.436	0	1
	price	Whether it mentions product price	0.659	0.476	0	1

[6] Literature suggests that 30 units are enough for a pretest [Lacy & Riffe 1996].
[7] The inter-judge reliability was calculated by a specialized software called ReCal [see Freelon 2010].

Table 2: Summary Statistics of Variables in Empirical Models

Variables	Description and Measurement	N	Mean	SD	Min	Max
sales	Product sales (in quantity) within four days around the product WeiTao marketing (in logs)	2104	1.402	1.717	0	8.606
Treat	Whether the product is promoted by WeiTao; equals 1 if the product is promoted by WeiTao and 0 otherwise	2104	0.500	0.500	0	1
After	Before or after WeiTao marketing; equals 1 for period after WeiTao marketing and 0 otherwise	2104	0.500	0.500	0	1
opentime	Store WeiTao opening date; take 1960/1/1 as benchmark (in logs)	2104	9.888	0.004	9.878	9.901
price	Product price (in logs)	2104	3.743	0.484	-0.968	8.188
color	Whether product has different colors or options; equals 1 if there are two or more colors/options and 0 otherwise	2104	0.375	0.484	0	1
delivery	Whether product is free shipping; equals 1 if shipping is not free and 0 otherwise	2104	0.591	0.492	0	1
collection	Number of consumers who bookmarked this product (in logs)	2104	4.126	2.372	0	10.044
comments	Number of received product comments (in logs)	2104	2.486	1.998	0	8.336
Informative	Informative content of a microblog; the first factor score of factor analysis	1052	0.147	0.846	-1.154	2.031
Persuasive	Persuasive content of a microblog; the second factor score of factor analysis	1052	0.042	0.888	-1.349	1.033
Promotional	Promotional content of a microblog; the third factor score of factor analysis	1052	0.081	0.758	-0.944	1.811
WordNum	Microblog length in the number of words (in logs)	1052	5.798	1.870	0	9.253

4. Empirical Results

4.1. Main Results of WeiTao Marketing at the Product-Level

Before we report results from our models, we first present model-free evidence using the average difference in product sales before and after WeiTao marketing and between the experiment group and control group, as shown in Table 3. As can be seen, before WeiTao marketing, there is no significant sales difference (-0.101) between the experiment group and the control group. However, after WeiTao marketing, the sales difference becomes significant (0.305, at the 1% significance level) between the two groups. For the experiment group itself, product sales increase 0.512 (significant at 1% level) from before to after WeiTao marketing. But the control group does not have significant sales increase (0.106 and insignificant) from before to after WeiTao marketing. This simple comparison analysis gives us a rough idea of the effect of social media MGC on product sales. More accurate estimation is through DID analysis that is presented in the following.

Table 3: Sales Comparison Before and After WeiTao between Experiment and Control Groups

	ln*sales*			
	Experiment Group	Control Group	Difference (Exp. - Control)	t-test
Before WeiTao	1.197	1.298	-0.101	-1.014
After WeiTao	1.709	1.405	0.305	2.752^{***}
Difference (*After - Before*)	0.512	0.106	0.406	
t-test	5.192^{***}	0.956		

Note： *** $p < 0.01$

We run DID regression of Equation (1) and results are shown in Table 4. We conduct four model variations presented as the four columns in the table. They are: basic model without any control variables, full sample analysis, sub-sample analysis for cosmetics products, and sub-sample analysis for stationery products. Overall, for all the four models, coefficient of the interaction term, *Treat*×*After*, is positive and significant, indicating a positive and significant WeiTao marketing effect on product sales.

In the simple model without control variables, coefficient of the interaction term *Treat*×*After* is 0.420 and significant at the 1% level. For the full sample analysis, coefficient of the interaction term *Treat*×*After* is 0.420 and significant at the 1% level. Results of control variables in the full sample analysis are consistent with our expectations. For instance, WeiTao opening date ln*opentime* has a negative coefficient (-8.979), which means the earlier the store opens WeiTao, the greater the WeiTao effect on product sales. Product price ln*price* has a negative and significant coefficient (-0.198, significant at the 5% level), meaning the lower the product price, the greater the WeiTao sales effect.

Considering the difference of WeiTao marketing effect between cosmetics (high-involvement) products and stationery (low-involvement) products, we conduct sub-sample analysis. As can be seen from Table 4, for cosmetics sub-sample, coefficient of the interaction term *Treat*×*After* is 0.367 and significant at the 1% level; whereas the stationery sub-sample has an even greater WeiTao effect of 0.569 and significant at the 5% level. To examine if the WeiTao effect in the stationery sub-sample is significantly greater than that in the cosmetics sub-sample, we follow the method proposed by Wooldridge [2002] — first, we construct a dummy variable, *industry*, which equals 1 if a store sells stationery and 0 if it sells cosmetics. Therefore, interaction term *industry*×*Treat*×*After* could capture the difference in WeiTao effect between the two industry sub-samples. And then, we add the dummy variable *industry* and the interaction term *industry*×*Treat*×*After* into Equation (1) and run the regression on the full sample. We find that coefficient of the interaction term *industry*×*Treat*×*After* is 0.503 and significant at the 1% level (not shown in the paper but available upon request), indicating that WeiTao effect is significantly greater for sales of stationery products than that of cosmetics products.

We further calculate sales elasticity of WeiTao marketing following Kennedy [1981]. It is 51.47% for the full sample, meaning that there is an average sales increase of 51.47% after WeiTao product marketing. The sales elasticity of WeiTao marketing for cosmetics products is 43.62%, whereas it is 67.08% for stationery products.

Table 4: DID Results for the Effect of WeiTao Marketing on Product Sales

	No Controls		**Full Sample**		**Cosmetics**		**Stationery**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Treat	-0.075	0.878	0.060	0.069	-.015	0.071	0.181	0.171
After	0.104	0.878	0.104	0.069	0.071	0.070	0.199	0.170
Treat×*After*	0.420^{***}	0.124	0.420^{***}	0.098	0.367^{***}	0.100	0.569^{**}	0.236
ln*opentime*			-8.979	8.403	-1.461	8.986	1.058	22.621
ln*price*			-0.198^{***}	0.023	-0.230^{***}	0.026	-0.189^{***}	0.066
delivery			-0.109	0.067	-0.069	0.066	-0.231	0.207
color			-0.149^{**}	0.061	-0.208^{***}	0.066	0.138	0.149
ln*collection*			0.045^{*}	0.024	0.016	0.025	0.141^{**}	0.063
ln*comments*			0.494^{***}	0.028	0.579^{***}	0.030	0.288^{***}	0.071
intercept	0.812^{***}	0.099	89.355	83.104	15.153	88.855	-10.014	223.752
N	2104		2104		1564		540	
# of Stores	123		123		102		21	

Note： *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

4.2. Results of the Content Effect of Social Media Marketing

For the experiment group, we further investigate if different types of social media marketing contents (i.e., informative, persuasive, and promotional contents) have different effects on product sales, and how such content effects vary with product categories. We conduct hierarchical regression to do so. First, we present the overall WeiTao marketing effect (with no content types) on product sales (i.e., Equation 2). It is shown in Table 5 with results from full sample, cosmetics sub-sample, and stationery sub-sample listed in separate columns. As can be seen, for all sample sets, coefficients of *After* are positive (full sample 0.549, cosmetics sub-sample 0.473, and stationery sub-sample 0.789) and significant at the 1% level. It suggests that social media MGC, in general, boosts product sales. Meanwhile, results of control variables are consistent with difference-in-differences results in Table 4.

Table 5: Effect of WeiTao Marketing on Sales of Experiment Products

	Full Sample		**Cosmetics**		**Stationery**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
After	0.549^{***}	0.073	0.473^{***}	0.081	0.789^{***}	0.163
ln*opentime*	-19.750	13.820	-27.477^{**}	13.915	58.664	41.899
ln*price*	-0.227^{***}	0.034	-0.258^{***}	0.040	-0.142	0.090
delivery	-0.101	0.099	-0.114	0.101	-0.056	0.300
color	-0.145	0.091	-0.188^{*}	0.103	0.010	0.213
ln*collection*	0.074^{*}	0.038	0.055	0.041	0.210^{**}	0.097
ln*comments*	0.465^{***}	0.046	0.510^{***}	0.050	0.266^{**}	0.113
intercept	195.955	136.678	272.528^{**}	137.604	-580.022	414.400
N	1052		782		270	
# of Stores	123		102		21	

Note： *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

And then, we investigate the content effect of MGC (i.e., Equation 3), and results are shown in Table 6. Comparing with results from Equation (2) in Table 5, after adding content types the coefficient of *After* becomes insignificant for all the three sample sets, i.e., full sample, cosmetics and stationery sub-samples. And the interaction terms between *After* and content types are significant (see details below). It indicates that the effect of WeiTao marketing is from the contents themselves.

For content effect, in the full sample analysis, coefficient of the interaction term *After*×*Informative* is positive 0.365 and significant at the 1% level. The other two interaction terms *After*×*Persuasive* and *After*×*Promotional* are not significant. Results indicate that, overall, informative social media marketing contents (such as information of product quality, product origins, and product functions) are more significant in influencing product sales than persuasive and promotional contents. However, in the sub-sample analysis, for different product categories (i.e., cosmetics vs. stationery), effect of content types is different. Specifically, results from cosmetics sub-sample are similar to that from the full sample analysis, that is informative contents are more effective. As for stationery sub-sample, persuasive content (such as pictures of products) and promotional contents (such as information of deals and free shipping) are more sales effective (with a coefficient of 0.408 and significant at the 10% level for persuasive content and a coefficient of 0.432 and significant at the 10% level for promotional content). Meanwhile, for both full sample and cosmetics sub-sample, coefficient of *After*×ln*WordNum* is positive and significant, suggesting the longer the WeiTao microblogs, the more helpful they are to the product sales.

Table 6: Effect of WeiTao Content Types on Sales of Experiment Products

	Full Sample		**Cosmetics**		**Stationery**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
After	-0.146	0.245	-0.505	0.355	1.333	0.814
After×*Informative*	0.365^{***}	0.078	0.542^{***}	0.084	-0.152	0.188
After×*Persuasive*	0.104	0.080	0.077	0.082	0.408^{*}	0.233
After×*Promotional*	0.111	0.078	0.004	0.085	0.432^{*}	0.242
After×ln*WordNum*	0.108^{***}	0.042	0.159^{***}	0.044	-0.066	0.105
ln*opentime*	-15.210	13.842	-23.278	14.467	50.650	44.117
ln*price*	-0.228^{***}	0.034	-0.252^{***}	0.039	-0.140	0.091
delivery	-0.126	0.096	-0.110	0.097	-0.054	0.306
color	-0.125	0.089	-0.162	0.099	0.033	0.211
ln*collection*	0.059	0.037	0.038	0.039	0.193^{**}	0.097
ln*comments*	0.471^{***}	0.045	0.515^{***}	0.048	0.267^{**}	0.112
intercept	151.189	136.886	231.121	143.058	-500.786	436.325
N	1052		782		270	
# of Stores	123		102		21	

Note： *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

To explain the above results between cosmetics products and stationery products, we think that buying cosmetics products, which are typical high-involvement products, usually requires more information for consumers to have a better understanding of the product to reduce purchase uncertainties. Therefore, informative contents provided by firm

MGC and the interactive feature of social media can enhance consumers' purchase intention and increase product sales. Whereas for stationery products, a low-involvement kind of product, consumers need relatively less product information and may focus more on peripheral information such as brand, appearance, and promotions. They tend to be attracted by promotional content such as deals and persuasive information such as living tips. Hence, promotional content and persuasive content posted by firm MGC marketing are more sales effective for low-involvement products.

4.3. Robustness Checks

To ensure our results, we conduct a few robustness checks starting from using different time windows to capture the sales effect. In the main model analyses presented above, we capture product sales in four days before and four days after WeiTao marketing. As a robustness, we use two other time windows, i.e., ± 2 days and ± 3 days, and re-run Equations (1) and (3), the two key models. For Equation (1) the DID analysis, full sample results (presented in Table 7) show that both ± 2 days time window and ± 3 days time window are consistent with our main model (i.e., the ± 4 days time window) results. The interaction term *Treat×After* is positive and significant at the 1% level for both time windows. Interestingly, we find that the longer the time window, the stronger the WeiTao marketing effect — coefficients of *Treat×After* in the time windows of ± 2 days, ± 3 days, and ± 4 days are 0.322, 0.382, and 0.420 (in Table 4), respectively, showing an increasing pattern. Meanwhile, robustness checks for the cosmetics sub-sample and stationery sub-sample are consistent, as presented in Table 8 and Table 9.

Table 7: Robustness Check for DID Analysis of WeiTao Marketing Effect on Full Sample

Full Sample	**Product Sales in ±2 Days**		**Product Sales in ±3 Days**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.
Treat	0.040	0.064	0.047	0.068
After	0.067	0.064	0.061	0.068
Treat×After	0.322^{***}	0.091	0.382^{***}	0.096
intercept	75.905^{***}	78.076	83.594^{***}	81.437
control variables	Included		Included	

Note: *** $p < 0.01$

Table 8: Robustness Check for DID Analysis of WeiTao Marketing Effect on Cosmetics Sub-Sample

Cosmetics	**Product Sales in ±2 Days**		**Product Sales in ±3 Days**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.
Treat	-0.038	0.067	-0.033	0.069
After	0.069	0.067	0.069	0.069
Treat×After	0.311^{***}	0.094	0.330^{**}	0.098
intercept	-0.721	81.642	-16.973^{***}	86.605
control variables	Included		Included	

Note: *** $p < 0.01$ ** $p < 0.05$

Table 9: Robustness Check for DID Analysis of WeiTao Marketing Effect on Stationery Sub-Sample

Stationery	**Product Sales in ±2 Days**		**Product Sales in ±3 Days**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.
Treat	0.180	0.154	0.189	0.166
After	0.061	0.151	0.038	0.162
Treat×After	0.352^{*}	0.213	0.529^{**}	0.230
intercept	52.856	208.022	72.129	215.580
control variables	Included		Included	

Note: ** $p < 0.05$ * $p < 0.1$

We further conduct robustness analysis using different time windows on Equation (3) for the effect of content types, and results are presented in Table 10. Again, results from the two different time windows are largely the same as our main model results. Overall, informative contents are more sales effective than persuasive contents and promotional contents.

Table 10: Robustness Check for Effect of WeiTao Content Types on Full Sample

Full Sample	**Product Sales in ±2 Days**		**Product Sales in ±3 Days**	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.
After×Informative	0.331***	0.071	0.297***	0.076
After×Persuasive	0.128*	0.073	0.106	0.078
After×Promotional	0.102	0.071	0.071	0.076
intercept	98.078	132.700	179.779	139.496
control variables	Included		Included	

Note: *** $p < 0.01$ * $p < 0.1$

We also conduct robustness check on product involvement for its effect on WeiTao marketing. In our main analysis, we use different product categories for product involvement, i.e., cosmetics products as high-involvement and stationery products as low-involvement. In robustness check, we use product price because it is an important proxy for product involvement according to the definition of product involvement [Assael 1984]. Usually, high-involvement products have high price tag for consumers, while low-involvement products have low price tag. We equally divide our cosmetics experiment group (we do the same thing on our stationery experiment group) into three sub-samples according to product price, and construct a dummy variable *highprice*, which equals 1 if the product's price belongs to the top one third, and 0 if product's price belongs to the bottom one third. Therefore, an interaction term *highprice×Treat×After* could capture the difference in WeiTao marketing effect between high-price sub-sample and low-price sub-sample. We add the dummy variable *highprice* and the interaction term *highprice×Treat×After* into Equation (1) to run the robustness check. The coefficient estimate of *highprice×Treat×After* is significantly negative for cosmetics products, which indicates that WeiTao effect is significantly greater for sales of low-price (proxy for low-involvement) products than that of high-price (high-involvement) products. The coefficient of *highprice×Treat×After* for stationery products is negative but insignificant, which indicates a similar price (product involvement) effect on WeiTao marketing to the cosmetics group, but the effect is less significant because the price differences among stationery products are relatively small.[8]

Moreover, we conduct robustness check on omitted variables such as product life cycle. We code information of product life cycle whenever it's available in product description and compare WeiTao marketing effect between newly launched products and the products that have been on shelf for a while. We find that WeiTao marketing has positive and significant sales effect for both types of products.[9] It indicates that product life cycle, an omitted variable, does not affect our results.

5. Discussions and Conclusions

In this study, we quantify the impact of firm social media MGC on sales at the product-level and examine the effect of MGC content types. The launch of WeiTao microblogging mobile platform on Taobao enables a quasi-experiment research design and we capture the value of firm social media MGC marketing through DID analysis. We find that overall social media MGC has positive and significant effect on product sales — on average, MGC leads to a 51.47% increase in product sales. Specifically, the MGC sales elasticity for low-involvement products is greater at 67.08%, and it is 43.62% for high-involvement products.

Based on MGC and advertising content literature, we classify our WeiTao contents into three types, i.e., informative, persuasive, and promotional. Content analysis shows that, in general, informative content is more effective in product sales than persuasive and promotional contents. When it comes to specific kind of products, informative content is more sales effective for high-involvement products, and persuasive content and promotional content are more sales effective for low-involvement products.

5.1. Theoretical Implications

Our study extends the research on social media MGC and contributes to the literature in the following ways. First, prior literature mainly focuses on the effect of consumer engagement on the overall firm sales [Dewan & Ramaprasad 2014; Rui et al. 2013]. We quantify the effect of firm social media marketing at the product-level because most MGC contents are product specific and this way gives us a more direct measure of MGC marketing performance.

Second, we investigate the effect of MGC content types, adding evidence to existing literature that hasn't drawn consistent conclusions. We find that, overall, informative contents are more effective generating new sales. However, persuasive and promotional contents are more effective for the sales of low-involvement products, which require less

[8] We did not provide table results here for sake of space, but they are available upon request.
[9] Detailed analysis results are available upon request.

informative information in the purchase decision process. Meanwhile, by coding social media MGC contents and classifying them using confirmatory factor analysis, we find a significant third type of marketing content — promotional content, which has been extensively used in China's social media MGC marketing practice, yet hasn't been identified in the literature [e.g. Bertrand et al. 2010; Liaukonyte et al. 2015]. Future studies with similar context may pay attention to promotional marketing content.

Third, we examine the role of product involvement in overall sales effect of social media marketing and in the contingency of content effect. Product involvement leads to different purchase decision processes and affects how MGC marketing influences consumers. We collect data from different product categories (representing different levels of product involvement), and believe our results are generalizable.

5.2. Managerial Implications

This study also has managerial implications that can be helpful for marketing practitioners. As firms continue their social media marketing efforts, they are curious about if and how their marketing activities take effect. However, it hasn't reached a clear understanding. Our findings may provide some guidance to social media marketing practice.

First, we find that social media MGC does have positive and significant effect on sales. In our research setting, MGC content can generate an average of 51.47% sales increase. This is an encouraging finding. Meanwhile, the effect of social media marketing varies with product category. It is greater for sales of low-involvement products. Thus firms may keep investing on social media marketing, and design appropriate marketing strategy according to their business characteristics.

Second, regarding marketing content effect, we find that informative content is more effective in general in stimulating product sales. For high-involvement products, social media marketing with more informative content could enhance brand and product awareness. Having such information could help consumers form a better understanding of the marketed product, reduce purchase uncertainties, and lead to stronger purchase intention and sales. Whereas for low-involvement products, persuasive and promotional contents are more attractive to consumers and effective in generating sales. Marketers can design proper marketing contents accordingly to have better marketing performance.

5.3. Limitations and Future Research

In summary, our study has potential contribution to social media marketing literature and practice. However, it has some limitations that hopefully can be overcome in future research. First, when conducting DID analysis, the control group is formed by using the function "consumers who viewed this item also viewed" of Taobao. Ideally, a more rigorous matching method such as propensity score matching (PSM) is preferred to identify the control product and handle the selection bias issue. However, because our experiment products are from different stores and there are limited number of similar products to the experiment product, we cannot perform PSM or other matching procedures. Under this situation, we think that the "consumers who viewed this item also viewed" function can give us a good alternative (i.e., the most similar one) to the experiment product. Second, the number of WeiTao microblogs we coded is rather small (i.e., 178 microblogs). This is due to the data access restriction on product sales by Taobao. We can no longer acquire product transaction history for all WeiTao marketed products. Thus we focus on those WeiTao microblogs with complete transaction data. However, our content coding and processing method can be applied to larger data set. In the future, if data allows, we could construct a bigger training set of WeiTao contents and use text mining techniques to identify content categories. Third, we only obtain one product category for high-involvement product and one product category for low-involvement product, i.e., cosmetics products representing high-involvement and stationery goods representing low-involvement. It is because for each product category, the data collection process involves a substantial amount of effort in collecting all WeiTao stores and retrieving all corresponding information. Later on, Taobao forbade data access to product sales history that restrained us from collecting more product categories. However, for sake of robustness, we have used product price as proxy of product involvement and divided cosmetics and stationery samples by price. We find consistent results to our main findings. In the future if data is available, we would expand our analysis and results could be more generalized.

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