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INVESTIGATING THE EFFECTS OF SELF-PRESENTATION AT SOCIAL NETWORK SITES ON PURCHASE BEHAVIOR: A TEXT MINING AND ECONOMETRIC APPROACH

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Abstract

With advances in information and communication technologies (ICT), companies and platforms look to use the increasing volume and diversity of user-generated content (UGC) to predict consumer behavior, but with mixed results. In this study, we propose a text mining technique to find support for self-presentation in online social media and show that this is correlated with the content producer's offline purchase behaviour. We use unique datasets from a social network site (SNS) and an offline fashion retailer to find that: 1) while public and private volume and sentiment metrics leads to non-significant predictions, the sentiment divergence can significantly explain offline purchases, 2) users who engage in SNS for self-presentation spend less money and buy less quantities, and 3) however, they spend more when exposed to specific site features that inspire self-presentation, like brand pages. Marketers and platform owners can benefit from our results by designing appropriate features to target such users.

Keywords: User-generated content, Information divergence, Self-presentation, Consumer behavior, Text mining.

1 INTRODUCTION

Social media has emerged as an important channel for bidirectional communication between businesses and consumers. Through online media such as user-review sites, *social network sites* (SNS), mobile applications, and discussion forums, the volume and diversity of consumer data has exploded (e.g., Liu et al., 2010). While users engage with brands on such platforms to seek and obtain various psychological gratifications as well as utilitarian benefits such as discounts and promotions, brands, too, have become increasingly conscious of the vast amount of *user generated content* (UGC) produced each day. Such information can be invaluable for consumer targeting and other brand marketing purposes (e.g., Archak et al., 2011; Chevalier et al., 2006; Liu, 2006).

While early studies show the potential of this public UGC to predict product success (e.g., Chevalier et al., 2006; Godes et al., 2004), more recent studies show mixed results (Wong et al., 2012). In perhaps one of the strongest evidences on the value of public UGC to predict consumer behavior and product sales, Goh et al. (2013) demonstrate that UGC valence on social network sites (SNS) may be up to 45 times as valuable as marketer-generated content in influencing consumer purchases. Similarly, studies by Dhar et al. (2009) and Ghose et al. (2011) have looked at UGC based metrics focusing primarily on publicly available data, e.g., analyzing blog posts to predict music sales (Dhar et al., 2009) or analyzing product ratings to predict consumer preferences (Ghose et al., 2011).

While previous studies have focused on the impact of public UGC on the behavior of the consumers who read or consume it through medium such as product reviews, little is known about the motivations to produce that content and its relationship to the authors' offline consumer behavior. Such insights can be valuable to marketers who want to target consumers on social media sites such as Twitter, Facebook, Instagram, Google+ and others, as well as other social media sites such as user-reviews sites, community forums, and social mobile applications. While other researchers suggest that individuals may be driven to produce public UGC under various motivations, this paper examines a previously unanswered question: What is the relationship between the public and private content generated by users on social media sites and *their own* offline purchasing behavior? We highlight an important aspect of social media data that has been overlooked in the existing marketing literature – the divergence of public and private communications among users on social media websites. We provide empirical evidence that those who produce UGC out of self-presentational motivations have a lower propensity to make offline purchases. We propose the divergence of public and private sentiment as a proxy for this self-presentational behaviour. We show that the divergence between private conversations and public content can explain offline purchase behavior of the content producers, while using only public or private UGC in isolation results in insignificant predictions. Our study shows that those who produce UGC with higher divergence of public and private sentiment have a lower propensity to make offline purchases.

Prior research provides several conflicting results with using solely public information. Evidence indicates that there are several confounding mechanisms at play, at times simultaneously, on the public stage. From herding behavior in individual decision making (Banerjee, 1992) to evidences of free-riding in social networks (Coleman, 1988), the public contributions we make are often deeply influenced by our peers. However, private communication can be more resilient to such direct peer-effects (Leary et al., 1990). In addition, ideas on this public-private dichotomy can be attributed to self-presentation theories and self-disclosure tactics stating that humans display divergent behavior in front of different audience groups (Leary, 1996; Goffman, 1959). Even though the difference in how users behave in their in-groups (private) vs. their out-groups (public) has been intensely studied in sociology and social psychology literature (see Brown, 2000 for a good review of studies based on social identity theory), the economics and marketing research literature have been silent on the implications of such theories in their own contexts. In the present study, we find that such theories might play an important role in the context of social media marketing. We depart from previous studies by empirically characterizing the impact of the divergence between the public and private activity of an online content producer on his offline purchasing behavior.

In this paper, using a unique dataset from a popular SNS and purchase data from a loyalty program of a fashion-apparel chain in an English speaking Asian country, we show that sentiment divergence of UGC can effectively explain the user's purchases at a brick-and-mortar store. We show that, however, only public content generated by these users on the SNS is not a significant predictor of their offline consumption. The results are equally grim when we use their privately-generated information as well. We use sentiment analysis on the public content and the private conversations to establish our divergence metric. Subsequently, we illustrate that a measure of the difference in sentiments between the public and private content, the user's "divergence," significantly explains the expenditure made and the total quantity purchased by the content producer. We suggest that this divergence metric may be an indicator for the user's innate need to self-present.

In summary, this study differs from prior studies in three major directions.

First, we focus our attention on individual-level sales transactions by the content producer rather than aggregate and product-level, and investigate whether a combination of public and private UGC is effective at explaining the offline behavior of the UGC producers. These findings can have strong implications for marketers and platform owners interested in performing behavioral targeting of its users.

Second, unlike past studies that correlate UGC characteristics to sales, we posit that the specific motivations behind content generation might be correlated with the offline purchasing behavior of the content producers. We base our analyses on two major motivations for generating public content - intrinsic motivations driven by utilitarian motives and image-seeking motivations which are driven by self-presentational motives (Toubia et al., 2013; Bughin, 2007). Empirically, we find that individuals on the SNS who have highly divergent sentiments spend less money and buy fewer products than those with lower sentiment divergence levels.

Third, while most previous research focuses exclusively on public content, we add to this public information, the user's private conversations. We find that the volume and sentiment of public and private UGC, when considered separately, do not explain the content producer's offline purchase behavior. However, the divergence of public and private sentiments effectively explains the same. We suggest that this may indicate self-presentational intentions. Our study contributes to the extant literature on UGC and consumer behavior by investigating the relationship between self-presentation behavior and purchase behavior. We use sentiment analysis to create a sentiment divergence metric as a proxy for such self-presentation. Our results extend the research on self-presentational motives, tactics and their social outcomes by providing empirical evidence of the economic outcomes of self-presentational behavior. By effectively utilizing users' content from multiple online channels to explain their offline behavior, our study demonstrates a viable method for behavioral targeting of users for marketers and platform owners.

2 RELATED WORK

In this section, we review past research on public UGC for prediction, self-presentation, and group-related influences.

2.1 Public User-generated Content and Inconsistent Value Predictions

The emergence of online communication and, in particular, on social media has dramatically increased online engagement and *word-of-mouth* (WOM), or user-generated content (UGC), on online platforms (Dellarocas, 2003). The WOM information comprises mainly of crowd-contributed reviews, ratings and social network chatter, which has been shown to display high predictive power. WOM interactions have been used to predict movie and television success (Rui et al., 2011; Chintagunta et al., 2010; Asur et al., 2010; Godes et al., 2004), election outcomes (Metaxas et al., 2012), product sales (Goh et al., 2013; Ghose et al., 2011; Chevalier et al., 2006; Chevalier et al., 2003) and even firm equity values (Luo et al., 2012). While most earlier studies on WOM have focused on the quantitative aspects of user-generated content (e.g., volume, ratings etc.), more recent studies have

shown that qualitative characteristics of the content (e.g., sentiment, readability, subjectivity etc.) have better predictive power (Goh et al., 2013; Zhang et al., 2012b; Ghose et al.,2012; Ghose et al.,2011).

On the other hand, a number of existing studies uncover the limitations of using social media data in predicting various offline outcomes. Among the notable ones, Wong et al. (2012) report that Twitter data should be used with caution and that Twitter users differ significantly from non-Twitter users in terms of their relative preferences (for movies in their case). The same study shows that a large volume of tweets does not necessarily predict box-office success as over half of them were found to be informationally irrelevant. In addition, while Asur et al. (2010) find the sentiment of tweets to be a strong predictor of movie success, several studies find that volume, and not valence, plays a vital role, implying thereby that any publicity is good publicity (Wasow et al., 2010). Such contradictions have surfaced in other contexts as well. Social media data was unable to predict pre-electoral polls in the US (O'Connor et al. 2010) and that the valence of consumer review text on product sites have been shown to have no correlations with actual sales (Liu et al.,2010; Liu 2006).

There are two major reasons as to why publicly observed WOM content may not be a good predictor of sales or success. We focus our attention on the motivations for users to generate UGC publicly. First, individuals are prone to self-presentational desires to varying extents (Baumeister, 1982). Thus, content contributed online might not necessarily be a result of an intrinsic motivation to generate content, but instead be reflective of a more *image-seeking* behavior (Toubia et al., 2013; Bughin, 2007). Second, content that is public in nature is subject to group related biases. In general, people have a tendency of modifying self-expressions to suit normative requirements (Schlenker, 1980; Jones et al., 1973). Thus there exists a significant and positive correlation between the actions of the individual and the actions of the group. We further discuss these motivations in the next two sections.

2.2 Self-presentation and Content Generation

Self-presentation theories highlight audience segregation as a key source of variation in the way we self-present (Leary, 1996; Goffman, 1959). Similarly, Rosenberg's Evaluation Apprehension Theory (Rosenberg, 1965) illustrate that humans behave differently when they perceive that they are being evaluated. The role of audiences in shaping self-expression is among the popular findings in impression management research (Baumeister et al., 1989; Schlenker, 1980; Jones et al., 1973). Since public channels in online ecosystem are under perpetual observation and evaluation, users might significantly alter their content production behavior to gain social acceptance and positive evaluation (Hogan, 2010; Marwick et al., 2010). This assertion is consistent with seminal studies in the area of social influence and social conformity (Cialdini et al., 2004; Asch, 1951).

Social media fosters self-presentational behavior. A key social media value offering is to enable users to efficiently broadcast their information (Toubia et al., 2013; Rui et al., 2011). As a result, it may attract users who are keen to self-present using such platforms. This need to self-present on social media sites has emerged as an important gratification sought by social media users (Donath et al., 2004; boyd, 2004). Users may self-present for several reasons like image construction, earning social status or to exert influence on others. However, while most social media websites are designed to encourage such self-presentational behaviors, as witnessed on online dating sites and photos sharing sites, some users may also be focused on more utilitarian purposes such as using health sites, reading blogs (Toubia et al., 2013; Carpenter, 2012), and joining brand-sponsored pages purely for discounts. While prior studies suggest that public content such as reviews, blog-posts and newsgroup conversations may have value to content consumers (Dhar et al., 2009; Chevalier et al.,2006; Godes et al.,2004), little is known about how utilitarian and self-presentational motivations to generate this public UGC influences the offline purchase behavior of the content producers. For some conspicuous domains such as fashion and apparel industries, we propose that users who produce content, i.e., the content producers, may be motivated by self-presentational desires which are also reflected in their offline and in-store purchasing behavior (Slama et al., 1999; Slama et al., 1995).

A key problem that arises in analysing data from such social media sites is in differentiating public content that is utility-driven versus that which is driven by self-presentational motivations. While

differentiating between these two competing motivations may be less critical from the content-consumer's perspective, it is crucial to making accurate predictions and for user targeting. For instance, a person who writes a positive movie review purely for publicity-seeking purposes might not have liked the movie or even seen it. However, if the same person writes the same review but driven purely by intrinsic motivations, then the review can be used to better predict his movie viewing history as well as the quality of the movie and its overall success. Hence, UGC can be effective in targeting marketing campaigns as well as at predicting sales, but only if the driving motivations are well understood.

2.3 Group-related Influences in Publicly Generated User Content

While self-presentational concerns have a significant influence on the semantics and sentiment of user generated content, a second important factor is the presence of group-related influences such as herding. In addition to the content producer's intrinsic motivation to produce UGC, users' public actions are likely to be strongly correlated with the behavior of the group (Hyman, 1942) due to herding behavior (Shiller, 1995; Banerjee, 1992; Bikhchandani, 1992). For example, Chen et al. (2011) establish the importance of observational learning in a group by showing that positive observational learning boosts product sales while negative observational learning has no similar effect. They suggest that the rationale is related to self-presentational motives. Similarly, through a series of experiments probing individual decision making in presence of a group, Asch (1951) uncovered strong evidences of conformity induced biases where the individual chose to follow the group decision even when the decision was clearly incorrect. These studies suggest that public content is rife with repetitive information which might not necessarily be indicative of the content producer's own preferences nor the product's attributes, but, rather, can be reflective of the overall group behavior.

In the online context and on social media sites, these studies indicate that a user's public and private content would be very different from each other owing to the presence of self-presentational and group-related concerns. In the absence of any such concerns, intrinsic motivations would dictate content generation and the public and private contents would be increasingly similar. However, if the user is more self-presenting, he may actively try to segregate content production based on his audience groups and this might lead to a higher divergence in the public and private content. Since the sentiment of content is an important qualitative attribute of the information, we would observe divergent public and private sentiments due to the different groups of audiences in the two channels. The present paper focuses on this self-presentation behavior which drives authors to post publicly such as on their profiles on SNS or, more generally, on other online communities. We suggest that using a combination of public and private data can be effective at consumer behavioral targeting or prediction in certain conspicuous domains such as the fashion and apparel industry.

3 DATA DESCRIPTION AND RESEARCH METHOD

We obtained purchase data of 2301 customers who belonged to a loyalty program of a popular brick-and-mortar fashion apparel retailer in an Asian country. The retailer has over 20 stores in the country selling men's, women's, and children's casual-wear clothes moderately priced, equivalently, between 8 and 77 USD. Customers are automatically enrolled into the loyalty program after spending a modest threshold amount on a single order. Thus, there are very limited self-selection concerns regarding the loyalty membership. The loyalty program provides discounted and money back incentives to use the loyalty member card, as well as "birthday promotions" and other services. The retailer also hosts a "brand page" on the SNS where they disseminate marketing messages and promotions to their followers. Through collaboration with the SNS, we obtained over 60,000 users' on the brand page. For those users, we collected backend social media activities including public content, such as postings on a user's profile, and private content such as user-to-user private conversations. This resulted in over 240 million pieces of textual content. We performed name and email matching to identify the 2301 users in our dataset, with about one year of SNS activity and offline purchases from November, 2010 to November, 2011.

In our subsequent empirical study we investigate whether the public and private social media content can predict offline consumer expenditure and purchase quantities. We then contrast these results with a model that uses a divergence measure of the user’s public-private sentiment to explain monthly expenditure and purchase quantities. For our analysis, we consider all content produced by the users and not just content produced by these users on the brand page. There are two reasons why we make this choice. First, we intend to show that individuals are innately self-presenting, even when they are not talking about fashion-related products. However, the level of self-presentation might change when these individuals join and produce content on the brand page. Second, there are significant data-sparsity issues with using content exclusively from the brand page, as not every individual produces content frequently on these pages. This makes it problematic to perform econometric modelling on such sparse data. Despite these constraints, our results provide insights for targeting new customer segments for SNS advertisers and sheds light into the motivation for users to produce UGC.

Based on past studies which suggest that users produce content on social media sites due to intrinsic or utilitarian motives and due to image-seeking desires (Toubia et al., 2013; Bughin, 2007), we hypothesize that a higher (lower) sentiment divergence between public and private disclosures among users is indicative of a higher (lower) desire to self-present. Table 1 provides the summary statistics. We show that public and private sentiment and volume of content taken exclusively are not capable of explaining consumer purchases. However, the sentiment divergence measure has stronger explanatory power. We show that customers who join the brand page on the SNS spend more prior to joining the brand page. However, on joining the brand page, their expenditure is moderated by their level of divergence i.e. high-divergent users spend more than low-divergent ones.

While several studies on self-presentation have looked at motives, the various tactics and their social outcomes, there have been limited focus on the economic outcomes of such self-presentational behaviors (Leary et al., 1990; Schlenker, 1986; Baumeister, 1982). Through the present study, we suggest that our sentiment divergence metric acts as a proxy for observing self-presentation behavior amongst content producers, and this proxy can explain their offline purchase behavior.

4 EMPIRICAL ANALYSES AND RESULTS

In this section, we investigate our sentiment divergence metric as a predictor of offline purchase as compared to models with only public or private content. First, we model the total monthly expenditure of the users based on the volume and sentiment of contribution in the public and private channels. We use the following panel *fixed* and *random* effects model specifications. Model (1) includes only public characteristics as regressors while model (2) includes both public as well as private. The results are shown in Table 2.

$$Expend_{it} = \beta_0 + \beta_1 * PubSent_{it-1} + \beta_2 * PubVol_{it-1} + \sum_{k=3}^7 \beta_k * Control_i + \alpha_i + \gamma_t + \delta_{it} \quad (1)$$

$$Expend_{it} = \beta_0 + \beta_1 * PubSent_{it-1} + \beta_2 * PriSent_{it-1} + \beta_3 * PubVol_{it-1} + \beta_4 * PriVol_{it-1} + \sum_{k=5}^9 \beta_k * Control_i + \alpha_i + \gamma_t + \delta_{it} \quad (2)$$

where, $Control_i = \{ Age_i, SNSAge_i, LoyaltyAge_i, PageViews_i, NumFriends_{it-1} \}$

Table 1 summarizes the regressors. We define $Expend_{it}$ as the total expenditure, measured in the local currency, made by consumer i in month t . $PubSent_{it}$ and $PriSent_{it}$ denote the total public and private sentiment scores for user i in month t for public content made on the user’s profile and private content through one-to-one messaging, respectively. A sentiment score of 0 denotes a neutral sentiment. Similarly, $PubVol_{it}$ and $PriVol_{it}$ denote the total volume of social media contributions for user i in month t for public and private content, respectively. To derive the sentiment scores, we favor a simple lexicon-based approach for sentiment mining (Li et al., 2010) over more complex machine-learning approaches because our algorithm is inherently map-reducible and hence can be employed in a scalable fashion with our dataset. For each piece of content, we generate a set of three scores viz. a

positive polarity score (*psent*), a negative polarity score (*nsent*) and an overall polarity score (*osent*) as the difference between the *psent* and *nsent*. We aggregate the *osent* per user-month across public and private content due to sparsity issues to produce the *PubSent_{it}* and *PriSent_{it}*, respectively.

Our models also include a number of control variables to account for some individual heterogeneity. *Age_i* and *SNSAge_i* control for the biological age, in years, of the user *i* as well as his tenure on the social media platform in number of days since he registered, respectively. Similarly, we define *LoyaltyAge_{it}* as the amount of time, in months, spent by the customer in the loyalty program of the retail store. The *NumFriends_{it}* variable controls for the number of friends, or “degrees,” of user *i* in month *t*. Lastly, we use *PageViews_{it}*, number of unique brand pages viewed by the user *i* on the social media platform at the time of recording the dataset, as a proxy for the level of activity on the SNS.

	Min	Max	Mean	Std. Dev.
Number of Users (Matched Content Producers and Loyalty Card Customers): 2301				
Period of observation: Nov, 2010 - Nov, 2011				
Dependent Variables:				
Total Monthly Expenditure (\$) (<i>Expend_{it}</i>)	0.000	1105.360	4.391	26.243
Total Monthly Sales (Quantity _{it})	0.000	70.000	0.265	1.631
Independent Variables:				
Total Public Sentiment Score (<i>PubSent_{it}</i>)	-98.000	398.000	8.407	17.795
Total Private Sentiment Score (<i>PriSent_{it}</i>)	-622.000	3776.000	10.364	62.303
Volume of public UGC (<i>PubVol_{it}</i>)	1.000	952.000	28.007	43.948
Volume of private UGC (<i>PriVol_{it}</i>)	1.000	6524.000	60.553	169.577
Mean Divergence Score (<i>MeanDiv_{it}</i>)	0.000	9.000	0.438	0.683
Standard Deviation of Divergence Score (<i>STDDiv_{it}</i>)	0.000	8.000	0.366	0.572
Age (years) (<i>Age_i</i>)*	13.000	106.000	31.295	8.635
SNS Tenure (days) (<i>SNSAge_i</i>)*	64.000	2441.000	1273.647	285.482
Store Loyalty Tenure (months) (<i>LoyaltyAge_{it}</i>)	0.000	129.000	12.975	16.035
Degree (<i>NumFriends_{it}</i>)	10.000	5234.000	399.212	351.000
SNS Activity (<i>PageViews_{it}</i>)*	0.000	6206.000	181.439	264.780

* cross-sectional value measured during the time period of data recording.

Table 1: Descriptive Statistics of Model Variables

The results in Table 2 show that neither the sentiment scores nor the volume for either the public or the private channel could significantly explain the total monthly expenditure of the content producers. This result shows that even after controlling for private conversations, the public content characteristics in terms of sentiment and volume were not able to explain the total offline purchases made by the content producers. This is likely due to the inherent biases associated with public UGC such as self-presentational concerns and herding as detailed in the previous section.

[Insert Table 2 about here]

Next, we compute the sentiment divergence scores *MeanDiv_{it}* and *STDDiv_{it}* for each user at a monthly level. We use this divergence as a proxy to capture the self-presentation behavior of content producers online. *MeanDiv_{it}* denotes the absolute difference between the mean of the public and private overall sentiment (*osent*) scores aggregated at a user-month level. Similarly, we add as a control the *STDDiv_{it}*, which denotes the difference between the standard-deviations of the public and private sentiment scores for a given user-month. These sentiment divergence metrics measure the amount of asymmetry in the users’ public and private sentiment for a given month. As discussed, we argue that users who have a higher score on these metrics may be more self-presenting in their social media behavior as compared to users who have a lower score. Thus, high divergent users tend to present content which is high in positive (negative) valence in public while simultaneously presenting high negative (positive) valence in private. Drawing on Goffman’s audience segregation (Goffman et al., 1959), we hypothesize that users choose to display this asymmetry vis-a-vis to present a suitable self-image to the different audience sets. Consequently, a high divergence may be an indication of a higher desire to self-present in individuals - those who are likely to develop and maintain multiple self-images

online in an effort to effectively maintain their self-concepts in front of different audience groups. In contrast, individuals with low-divergence have low levels of audience segregation i.e. their public and private self-images are similar. These individuals are not as self-presenting and might use social media platforms to seek more utility-related gratifications like information and entertainment (Park et al., 2009). To investigate the effects of divergence on purchasing behavior, we employ a fixed-effect (FE) and random-effect (RE) estimation strategy as follows:

$$\begin{aligned}
Expend_{it} = & \beta_0 + \beta_1 * PubSent_{it-1} + \beta_2 * PriSent_{it-1} + \beta_3 * PubVol_{it-1} + \beta_4 * PriVol_{it-1} + \\
& \beta_5 * MeanDiv_{it-1} + \beta_6 * STDDiv_{it-1} + \sum_{k=7}^{11} \beta_k * Control_i + \alpha_i + \gamma_t + \delta_{it}
\end{aligned} \tag{3}$$

where, $Control_i = \{ Age_i, SNSAge_i, LoyaltyAge_{it}, PageViews_i, NumFriends_{it-1} \}$

Given that self-presentation drives purchase behavior, the act of joining brand pages should influence more self-presenting users differently than the less self-presenting users. Specifically, we hypothesize that while low-divergent users might be attracted to the more utilitarian aspects of joining the brand page (i.e. staying informed about price promotions, offers etc.), high-divergent users might be more attracted because the brand-attachment helps in their self-image building. Consequently, the low-divergent users joining the brand page would end up spending less than the high-divergent users. In the following model, we introduce a brand page dummy to denote whether the user is a member of the brand page or not at time t .

$$\begin{aligned}
Expend_{it} = & \beta_0 + \beta_1 * PubSent_{it-1} + \beta_2 * PriSent_{it-1} + \beta_3 * PubVol_{it-1} + \beta_4 * PriVol_{it-1} + \\
& \beta_5 * MeanDiv_{it-1} + \beta_6 * STDDiv_{it-1} + \beta_7 * BrandPageJoin_{it} + \\
& \beta_8 * MeanDiv_{it-1} * BrandPageJoin_{it} + \sum_{k=9}^{13} \beta_k * Control_i + \alpha_i + \gamma_t + \delta_{it}
\end{aligned} \tag{4}$$

where, $Control_i = \{ Age_i, SNSAge_i, LoyaltyAge_{it}, PageViews_i, NumFriends_{it-1} \}$

The estimation results are shown in Table 3. We observe that the main effect variables for the mean divergence score and the brand page join dummy are both negative and significant. The negative relationship with divergence indicates that, all else remaining constant, high divergent individuals on social media platforms spend less than low divergent individuals. There may be several reasons as to why we observe this effect in our data. Since high-divergent individuals are hypothesized to be more self-presenting, their main reason for purchasing fashion products is to help maintain their self-image in public. Thus, even though these individuals are members of the loyalty program of our retailer, they are likely to have similar memberships with several other competing retailers to keep track of emerging fashion choices. As a result, their expenditures are likely to get distributed among several retail stores leaving a lower expenditure amount for any one of them. Second, we argue that product purchase and consumption is, at times, treated as a self-presentational tactic in itself by individuals (Slama et al., 1999; Slama et al., 1995). Yet, little is known about whether self-presentation on social media sites has a complimentary or substitutional effect for offline activities including purchases. On the one hand, individuals who are already self-presenting offline might experience a lesser need to self-present using other modes such as on social media platforms, having already self-presented in real life. Consequently, individuals who do not display such self-presentation behavior offline might choose to repair their self-image online by displaying divergent UGC behavior. Such audience transfer effects are commonly reported in self-presentation literature (Steele, 1975; Apsler, 1975).

The negative and significant relationship on the brand-page join dummy can be explained by understanding the reasons why people join a brand page on social media platforms. A recent study showed that 42% of users who “liked” a brand fan-page on the popular social network site Facebook did so because they expected promotions and offers¹. A similar study reported that 52% of all fans of travel-related brand pages on social media sites like Twitter or Facebook “liked” the pages in hopes of better discounts². The same study showed that companies are aware of this trend and around 77% of all content displayed on these brand pages pertained to promotional coupons. Therefore, it may be that individuals who join the brand page are better exposed to product discounts and they end up spending less for their purchases than social media members who are not members of the brand page i.e. not “fans”. The interaction between joining the brand page and the divergence, however, provides a counterintuitive insight - that even though member of brand page spend less than non-members, this effect is moderated by the level of divergence of the brand page members. More specifically, high-divergent brand page members spend more than low-divergent brand page members. These results are consistent with a study which finds that 31% and 27% of the users mentioned that they “liked” brand pages to “share personal good experiences” and to share their “interests/lifestyles with others” respectively². These people are deemed to be more self-presenting than others who join the fan-page for utilitarian reasons such as discounts. Thus, we find empirical support that even though many users might join brand pages for discounts, those who do so due for strong self-presentational desires, our high divergent individuals, end up spending more than others with less of such aspirations.

[Insert Table 3 about here]

Finally, we investigate the robustness of our model to alternate operationalizations of purchasing behavior. We use sale quantity as a dependent variable to rule out a potential confound that high-expenditure might be caused due to the high price of the items purchased and it is not necessarily indicative of increased purchasing propensity. We specify a similar set of models, but using quantity as the dependent variable:

$$Quantity_{it} = \beta_0 + \beta_1 * PubSent_{it-1} + \beta_2 * PriSent_{it-1} + \beta_3 * PubVol_{it-1} + \beta_4 * PriVol_{it-1} + \beta_5 * MeanDiv_{it-1} + \beta_6 * STDDiv_{it-1} + \sum_{k=7}^{11} \beta_k * Control_i + \alpha_i + \gamma_t + \delta_{it} \quad (5)$$

$$Quantity_{it} = \beta_0 + \beta_1 * PubSent_{it-1} + \beta_2 * PriSent_{it-1} + \beta_3 * PubVol_{it-1} + \beta_4 * PriVol_{it-1} + \beta_5 * MeanDiv_{it-1} + \beta_6 * STDDiv_{it-1} + \beta_7 * BrandPageJoin_{it} + \beta_8 * MeanDiv_{it-1} * BrandPageJoin_{it} + \sum_{k=9}^{13} \beta_k * Control_i + \alpha_i + \gamma_t + \delta_{it} \quad (6)$$

where, $Control_i = \{ Age_i, SNSAge_i, LoyaltyAge_i, PageViews_i, NumFriends_{it-1} \}$

The FE and RE estimation results are illustrated in Table 4. The results are consistent with the ones we obtained with Models 3 and 4. As expected, we find a significant interaction effect of the mean divergence score and the brand page join dummy.

[Insert Table 4 about here]

5 CONCLUSIONS

This study bridges three major gaps in the current marketing and information systems literature. First, while past research have focused on the effects of user-generated content (UGC) on content consumers on product adoption and economic outcomes, this is among the first studies to investigate the content producers’ economic value and their offline purchasing behavior. While prior studies

¹ <http://www.syncapse.com/why-consumers-become-facebook-brand-fans/#.UrvN0OKXN8G>

² <http://www.tnooz.com/article/why-do-consumers-follow-or-like-travel-brands-in-social-media-for-the-discounts-alas/>

have focused on the content consumer's perspective, recent studies seem to indicate that content producers are equally, and perhaps more, valuable to the platform owners (Zhang et al., 2012a). Second, our studies uncover the importance of investigating the economic value of information divergence in UGC at the individual level - an issue that existing studies seem to have not focused on. In particular, users may actively self-select into the SNS for self-presentational motives. Hence, using public or private content exclusively in isolation from each other would lead to inconsistent predictions of purchase behavior and economic outcomes. We contend that individual differences in self-presentation and utilitarian motivations can be operationalized when we compute a divergence metric from the user generated content. Our results provide not only theoretically interesting insights about how self-presentation might impact economic outcomes, but are also important for practitioners looking to target and attract valuable customers. We use purchase data from a brick-and-mortar store to show that users who have a higher need to self-present tend to buy and spend more when they join brand pages on social media platforms when compared to their more utility-driven counterparts. However, there exists a dilemma around how marketers might operationalize divergence similar to what we have computed in our models. While it may not be feasible for marketers, with notable exceptions, to have access to private user data of their customers, we argue that advertisers might choose to invest more in websites that are fundamentally more attractive to self-presenting individuals as compared to other websites because of certain features. Furthermore, platform owners can design these features into their SNS that caters to certain individuals over others to increase the economic value to their advertisers. Third, and importantly, this paper makes a methodological contribution by showing that using a simple measure of sentiment divergence, we are able to explain offline purchases made by the content producers.

On a theoretical front, this paper finds empirical support for self-presentation behavior and its effects on purchase behavior. Furthermore, it extends past research on impression management by illustrating that self-presentation has tangible economic outcomes at the individual level.

While our results are promising and shows the value of text mining for behavioral targeting, our present study has a number of limitations which we seek to address in future studies. First, our current data context includes user data from just one, albeit large and popular, SNS and its associated brand page. Second, we currently lack purchase data from other fashion retail stores in the same region. While we conjecture that low expenditure by high-divergent users on one platform might indicate that their overall spending is distributed among multiple stores, our current dataset limits us from establishing this empirically. Third, we use data from a popular fashion apparel store prone to certain product characteristics distinct from other consumer goods. Thus, there might be unobserved taste shocks relevant to these types of products that are visible to the consumer, but not to the econometrician. Fourth, we use divergence as a simple proxy to observe the self-presentation behavior. However, we do not differentiate between specific modes of self-presentational behavior like acquisitive or protective self-presentations for instance (Slama et al., 1999; Slama et al., 1995). We believe that identifying these tactics from consumer data and correlating them with purchase information might provide a fruitful direction for future research. Finally, since we perform matching of user data from two distinct sources viz., the offline loyalty program and the online brand page, there might be potential self-selection concerns that might bias our findings. For instance, users who choose to self-select into the online brand page might not be representative of all social media users. In addition, customers might also choose to self-select into the loyalty program of the retailer. Although we argue that this might not be a major source of self-selection bias as most customers are enrolled automatically into the program, there might still be certain demographic differences between the loyalty program members and non-members. To address these concerns, we are presently running two-stage Heckman selection models (Heckman, 1979) with suitable user-level covariates to correct for these biases. Our initial results show that even after correcting for these potential selection biases, the results are consistent with the ones reported in our study.

Predictors	1(a): Expend_{it} (FE)	1(b): Expend_{it} (RE)	2(a): Expend_{it} (FE)	2(b): Expend_{it} (RE)
PubSent _{it-1}	-0.006 (0.014)	0.002 (0.011)	-0.005 (0.014)	0.003 (0.012)
PriSent _{it-1}			-0.002 (0.003)	-0.001 (0.003)
PubVol _{it-1}	-0.004 (0.008)	-0.005 (0.005)	-0.004 (0.008)	-0.005 (0.005)
PriVol _{it-1}			0.0001 (0.001)	-0.0001 (0.001)
Age _i	-	0.057** (0.025)	-	0.060** (0.025)
SNSAge _i	-	(omitted) [#]	-	-0.001 (0.001)
LoyaltyAge _{it}	-0.699*** (0.079)	0.013 (0.013)	-0.699*** (0.079)	0.015 (0.013)
NumFriends _{it-1}	0.019*** (0.003)	-0.0001 (0.0006)	0.020*** (0.003)	-0.0001 (0.001)
PageViews _i	-	-0.0004 (0.001)	-	-0.0004 (0.001)
Intercept	-0.008 (1.338)	-1.592 (1.079)	-0.006 (1.341)	0.031 (1.616)
Month Dummies	Present	Present	Present	Present
Observations:	16,735	16,735	16,735	16,735
Number of Consumers:	1,904	1,904	1,904	1,904
R-squared	0.097	0.092	0.097	0.092
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note:

i. The subscript t-1. for the first few predictors indicates that the variable is lagged by 1 time period. This is done to avoid concerns involving reverse causality in the same time period.

ii. All measures of Standard Errors reported are robust.

iii. A post-estimation Hausman Test was performed on FE and RE estimation results to evaluate the consistency of the alternate estimator and only the FE estimator was found to be consistent.

[#] SNSAge was found to be strongly collinear with the NumFriends variable and hence dropped from the estimation.

Table 2: Public and Private predictors of Total Expenditure

Predictors	3(a):Expend_{it} (FE)	3(b): Expend_{it} (RE)	4(a): Expend_{it} (FE)	4(b): Expend_{it} (RE)
PubSent _{it-1}	-0.002 (0.014)	0.007 (0.012)	-0.001 (0.014)	0.007 (0.012)
PriSent _{it-1}	-0.001 (0.003)	-0.0001 (0.003)	-0.001 (0.003)	-0.0003 (0.003)
PubVol _{it-1}	-0.006 (0.008)	-0.007 (0.005)	-0.005 (0.008)	-0.008 (0.005)
PriVol _{it-1}	-0.00003 (0.001)	-0.0003 (0.001)	-0.0001 (0.001)	-0.0003 (0.001)
MeanDiv _{it-1}	-0.589* (0.320)	-0.611** (0.293)	-1.682** (0.597)	-1.220** (0.555)
STDDiv _{it-1}	-0.136 (0.346)	-0.178 (0.323)	-0.116 (0.345)	-0.159 (0.323)
Age _i	-	0.061** (0.025)	-	0.054** (0.025)
SNSAge _i	-	-0.001 (0.001)	-	-0.001 (0.001)
LoyaltyAge _{it}	-0.700*** (0.079)	0.015 (0.013)	-0.628*** (0.080)	0.022 (0.013)
NumFriends _{it-1}	0.019*** (0.003)	-0.0002 (0.001)	0.023*** (0.003)	-0.00001 (0.001)
PageViews _i	-	-0.0005 (0.001)	-	-0.001 (0.001)
BrandPageJoin _{it}			-4.603*** (0.699)	-2.342*** (0.537)
BrandPageJoin _{it} *			1.428** (0.662)	0.778 (0.618)
MeanDiv _{it-1}				
Intercept	0.352 (1.357)	0.399 (1.624)	1.479 (1.378)	1.943 (1.665)
Month Dummies	Present	Present	Present	Present
Brand Page Dummy	Absent	Absent	Present	Present
Observations:	16,735	16,735	16,735	16,735
Number of Consumers:	1,904	1,904	1,904	1,904
R-squared	0.098	0.092	0.100	0.094
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note:

- i. The subscript t-1 for the first few predictors indicates that the variable is lagged by 1 time period. This is done to avoid concerns involving reverse causality in the same time period.
- ii. All measures of Standard Errors reported are robust.
- iii. A post-estimation Hausman Test was performed on FE and RE estimation results to evaluate the consistency of the alternate estimator and only the FE estimator was found to be consistent

Table 3: Public, Private and Divergence predictors of Total Expenditure

Predictors	5(a): Quantity _{it} (FE)	5(b): Quantity _{it} (RE)	6(a): Quantity _{it} (FE)	6(b): Quantity _{it} (RE)
PubSent _{it-1}	-0.00002 (0.001)	0.001 (0.001)	- 0.0001 (0.001)	0.0006 (0.001)
PriSent _{it-1}	-0.00004 (0.0002)	0.00003 (0.0002)	-0.00005 (0.0002)	0.00002 (0.0002)
PubVol _{it-1}	-0.001 (0.0005)	-0.001* (0.0003)	- 0.001 (0.0005)	-0.001* (0.003)
PriVol _{it-1}	-0.0001 (0.0001)	-0.00003 (0.0001)	-0.00004 (0.0001)	-0.00003 (0.0001)
MeanDiv _{it-1}	-0.036* (0.020)	-0.038** (0.018)	-0.110*** (0.036)	-0.084** (0.034)
STDDiv _{it-1}	-0.010 (0.021)	-0.010 (0.020)	-0.008 (0.021)	-0.009 (0.020)
Age _i	-	0.004*** (0.001)	-	0.004** (0.001)
SNSAge _i	-	-0.00002 (0.0001)	-	-0.00002 (0.0001)
LoyaltyAge _{it}	-0.040*** (0.005)	0.003* (0.001)	-0.037*** (0.005)	0.002** (0.001)
NumFriends _{it-1}	0.001*** (0.0002)	-0.00003 (0.00004)	0.001*** (0.0002)	-0.00002 (0.00004)
PageViews _i	-	-0.00002 (0.00004)	-	-0.00003 (0.00004)
BrandPageJoin _{it}			-0.248*** (0.043)	-0.107*** (0.032)
BrandPageJoin _{it} *			0.096** (0.040)	0.059 (0.038)
MeanDiv _{it-1}				
Intercept	-0.007 (0.083)	-0.054 (0.094)	0.060 (0.084)	0.018 (0.096)
Month Dummies	Present	Present	Present	Present
Brand Page Join Dummy	Absent	Absent	Present	Present
Observations:	16,735	16,735	16,735	16,735
Number of Consumers:	1,904	1,904	1,904	1,904
R-squared	0.103	0.098	0.105	0.099
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note:

- i. The prefix t-1 for the first few predictors indicates that the variable is lagged by 1 time period. This is done to avoid concerns involving reverse causality in the same time period.
- ii. All measures of Standard Errors reported are robust.
- iii. A post-estimation Hausman Test was performed on FE and RE estimation results to evaluate the consistency of the alternate estimator and only the FE estimator was found to be consistent

Table 4: Public, Private and Divergence predictors of Total Sale Quantity

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