The Untold Story of Social Media on Offline Sales: The Impact of Facebook in the U.S. Automobile Industry

Research-in-Progress

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Abstract

Facebook has become a leading avenue for online brand communities (i.e., fan pages) that are used for marketing purposes. Despite the popularity on Facebook, there has been limited empirical research regarding the dynamics of firm-generated content (FGC) and user-generated content (UGC) over a long period of time at the industry level. The objective of this paper is to examine the dynamics of the interactions between FGC, UGC, and offline sales (light vehicles) in the U.S. automobile industry. We collected detailed data including the official Facebook pages of 31 car makes in the U.S., and supplemented the data from these firms' traditional media efforts, and offline car sales from 2009 to 2014. We employ a panel vector autoregressive (PVAR) model that allows us to investigate the dynamic relationships among multiple time series variables. The preliminary analysis results, expected contributions, and future plans are discussed.

Keywords: Facebook, firm-generated content (FGC), user-generated content (UGC), offline sales, U.S. automobile industry

Introduction

Deloitte's recent report on Facebook indicates that Facebook added $227 billion to the global economy and helped to support 4.5 million jobs around the world in 2014 (Deloitte 2015). In particular, 100 billion of the economic impact affects the US, where Facebook also helped to support more than 1 million jobs, followed by the UK as the second-biggest benefactor of Facebook (Deloitte 2015). Due to its significant impact, Facebook has become a leading avenue for online brand communities (i.e., fan pages) that are used for marketing purposes (Facebook 2015; Goh et al. 2013). At a firm’s Facebook page, both firms and users can generate contents to interact with firms or other users (hereafter termed as firm-generated content (FGC) and user-generated content (UGC)). To influence customers’ purchase decisions, firms engage in advertising, products/services, deals, and customer relationship. At the same time, customers also get easier access to express their personal experience. Despite the popularity on Facebook, there has been limited empirical research regarding the dynamics of FGC and UGC with the exception of Goh et al. (2013). First, while prior research has well documented the economic impact of various aspects of UGC (e.g., Ghose and Ipeirotis 2011), none have examined the dynamic relationship between FGC, UGC, and offline product sales in the context of a social media brand community. Second, most studies only focus on the impact of social media on online sales (e.g., Chen et al. 2015; Ghose and Ipeirotis 2011; Stephen and Galak 2012). Third, the
extant literature examines the impact of social media exclusively either over a short duration of time (e.g., Chen et al. 2015; Dewan and Ramaprasad 2014) or in a single firm (e.g., Goh et al. 2013; Stephen and Galak 2012). Little effort has been devoted to understanding how FGC, UGC, and offline sales interact over a long period of time at the industry level.

The objective of this work is to assess the dynamics of the interactions between FGC, UGC, and offline sales (light vehicles) in the U.S. automobile industry. The U.S. automobile industry is ranked the second highest industry in digital advertising spending (eMarketer 2015) and the highest one in both traditional and digital advertising spending (Nielsen 2015). Despite the large amount of spending in digital advertising, no empirical research examines the relative effectiveness of FGC and UGC on offline car sales in the setting of the firm-initiated Facebook page. Therefore, this study aims to answer the following research questions:

- Do FGC and UGC have an effect on offline car sales, after controlling for other influential factors such as traditional media spending?
- What are the dynamics of the relationship between FGC, UGC, and offline car sales?

To answer the above questions, we collected detailed data including the official Facebook pages of 31 car companies in the U.S., and supplemented the data from these firms’ traditional media efforts, and offline car sales (which typically occur through dealerships) from 2009 to 2014. We collect not only FGC and UGC posts but also four common types of posts at Facebook (i.e., link, photo, status, and video). Our empirical analysis is conducted using the panel vector autoregressive (PVAR) model at both the post-level and the type of post-level. The PVAR approach allows us to (1) treat all of the major variables (FGC, UGC, and offline car sales) as jointly endogenous, and assess the nature of bidirectional causality between all pairs of variables, in addition to controlling for a variety of factors that can affect offline car sale and (2) examine lagged effects within and across time series to understand the dynamic relationships between all variables.

**Literature Review**

Several studies have examined the impact of online word-of-mouth (WOM) or UGC on sales. For example, Forman et al. (2008) posit that reviews posted by reputable reviewers have greater impact on product sales than those by less reputable reviewers. Ghose and Ipeirotis (2011) find that reviews that have a mixture of objective, and highly subjective sentences are negatively associated with product sales, compared to reviews that tend to include only subjective or only objective information. Rui et al. (2013) examine the effect of Twitter messages on movie sales and suggest that valence of the tweet, influence level of the tweeter, and the intention expressed by the tweeter to what a specific file all influence sales. The discussion of the relative impact of FGC and UGC on sales is very rare, particularly on their relative impacts on offline product sales. For example, Mayzlin (2006) develops an analytical model to examine the credibility of online WOM and finds that consumer WOM can still be persuasive despite the overt promotional intent by firms. Albuquerque et al. (2012) measure the value of promotional activities and referrals by content creators and compare these activities with firm-based actions (e.g. public relations). However, their study does not focus on FGC per se. A recent study by Goh et al. (2013) is highly related to our research context. They study the relative impacts of FGC and UGC on sales in the setting of a casual wear apparel retailer’s Facebook page. However, their study (1) only focus on a single company in a small Asian market, (2) does not capture the lagged effects when the effects of marketing activities on sales are studied (e.g., the lagged effect of sales on FGC and UGC), (3) do not consider the role of different types of posts (i.e., link, status, photo, and video) on sales, (4) do not examine the effects of the post content (i.e., positive and negative posts) on sales, and (5) do not explore the effects of all Facebook features (i.e., likes, comments, and shares) on sales.

Several studies apply VAR (Vector Autoregressive model) or PVAR to study dynamic interactions among several variables of interest. For example, Luo et al. (2013) explore the dynamic interactions between social media-based metrics (i.e., Web blogs and consumer ratings), conventional online behavior metrics (Google searches and Web traffic), and firm equity value. Their results indicate that conventional online behavior metrics have a significant yet substantially weaker predictive relationship with firm equity value than social media metrics. Dewan and Ramaprasad (2014) examine the relationship between social media in the form of blog, traditional media, and sales in the context of the music industry. They find that radio play is consistently and positively related to future sales at both the song and album levels. Blog buzz, however, is not related to album sales and negatively related to song sale. Finally, Chen et al. (2015) employ PVAR models to investigate the inter-relationship between broadcasting promotions and music sales and find that music sales are positively associated with bulletins’ updates on the artist’s profile pages.
Research Model and Hypotheses

The conceptual framework of this research-in-progress is shown in Figure 1. For FGC and UGC, we are interested in their effects at two different levels: post and type of post (i.e., link, photo, status, and video). Previous research indicates that information representation formats (e.g., text, graphic, or video) do matter in influencing people’s decision-makings (Lim and Benbasat 2000; Nah et al. 2011). Therefore, we consider the role of the post type in our model.

The impact of social media on sales has been well documented in prior research (e.g., Chen et al. 2015; Dewan and Ramaprasad 2014; Duan et al. 2008). For example, Onishi and Manchanda (2012) examine the impact of blogging on sales of three products in Japan and find a clear relationship between blogging volume and valence on product sales. To attract more visitors and influence customers’ purchase decisions at the firm-initiated Facebook page, firms engage in advertising, products/services, deals, and customer relationship. At the same time, customers can also easily engage in either customer-to-customer or customer-to-firm communications. Due to this simultaneous engagement of customers and firms at the firm-initiated online community, both FGC and UGC influence consumers’ purchase decisions (Goh et al. 2013; Rishika et al. 2013). Thus, we hypothesize:

\[ H_1: \text{The volume of firm-generated content is positively associated with offline car sales} \]

\[ H_2: \text{The volume of user-generated content is positively associated with offline car sales.} \]

Dewan and Ramaprasad (2014) study the interplay between blog buzz, radio play, and music sales and find that album sales are positively related to blog buzz. Stephen and Galak (2012) explore the effects of traditional and social media on loan sales and indicate that repeat loan sales are positively associated with the volume of blogs. We posit that there is a positive relationship from offline sales to both UGC and FGC in the setting of the firm-initiated Facebook page. An increase in firm sales can raise the firm’s brand recognition and appreciation on the Facebook page so that both firms and customers are more likely to disseminate their products related information and brand experience. An increase in firm sales implies that firm needs to maintain or enhance its current customer-firm relationships to sustain its competitive advantage. Therefore, it is plausible that an increase in sales will trigger firms to have a more active and vibrant Facebook community with regular new postings. Such an active approach also allows customers to infer the level of a firm’s relationship commitment and therefore strengthens customers’ bond with the firm (Rishika et al. 2013). Consumers often love to share and relate their product experiences with members of a brand community (Algesheimer et al. 2005). In addition, individuals also wish to validate their choices in an environment that further strengthens their own affinity with the firm (Zhu et al. 2010). Therefore, it is intuitively logical that an increase in sales will drive more UGC. As a result, we hypothesize:

\[ H_3: \text{Offline car sales are positively associated with the volume of firm-generated content.} \]

\[ H_4: \text{Offline car sales are positively associated with the volume of user-generated content.} \]

The firm-initiated Facebook page creates a channel for communicating with its customers and building relationships with them (Miller and Tucker 2013). An active social media page with regular new messages/postings can help customers form more positive attitudes toward the firm and therefore increase the interactions between firms and customers (Rishika et al. 2013). These increased interactions are essential to form customer identification with the firm and can create greater trust to the firm and customer loyalty (Algesheimer et al. 2005). Prior research in relationship marketing claims that commitment and trust are two critical components for a party’s intentions to continue the relationship with the other part (Morgan and Hunt 1994). Therefore, in the setting of the firm-initiated
Facebook page, if firms can interact their customers actively by providing more products/services information, customer are more likely to get involve in the interaction with firms as well as other customers. In addition, Miller and Tucker’s study (2013) on social media management provide empirical evidence that actively managing a Facebook page (i.e. updating status more frequently) increases the amount of UGC. Therefore, we hypothesize:

**H5: The volume of firm-generated content is positively associated with the volume of user-generated content.**

Previous research indicates that UGC changes sellers’ communication strategy to best respond to those user-based reviews (Chen and Xie 2008). We argue that more UGC drives more FGC. UGC is a direct expression of consumers’ personal experience toward firms’ products or services (Goh et al. 2013) and therefore allows firms to better realize their customers’ preferences. In the context of a firm-initiated Facebook page, if a large number of consumers exhibit favorable attitudes and sentiments toward a product or service, firms are more likely to disseminate more information related to that product or service to enhance customer relationship. The extant literature claims the importance of active social media management and suggests that firm postings need to be specifically targeted to clients’ interests (Miller and Tucker 2013). One of the key approaches for firms to generate targeted content is through the learning of UGC at firm-initiated Facebook pages. Thus:

**H6: The volume of user-generated content is positively associated with the volume of firm-generated content.**

### Empirical Methodology

#### Data

Our samples consist of 31 major car makes in the U.S. automobile industry (10 US-based, 9 European-based, and 12 Asia-based makes; see appendices for the completed list). We use three main data sources for our panel, namely, the Facebook graph API (Application Programming Interface) for FGC and UGC, monthly offline car sales from the WardsAuto Premium database, and traditional media advertising expenditure (i.e., TV, radio, magazines, newspapers, and outdoor displays; see appendices for the completed list) from an ad intelligence company called Kantar Media. We also collected the consumer search volume index from Google Trends to control for the popularity effect of each car make (Luo et al. 2013). Finally, we collected some macroeconomic indicators to control for their potential impacts on offline car sales. These indicators include the monthly gasoline price index from U.S. Bureau of Labor Statistics, the conference board’s consumer confidence index, and S&P 500 monthly return.

Since we are interested in how firm’s initiated Facebook page influences offline sales over time, we, therefore, collected data from the beginning of each firm-initiated Facebook page. Specifically, we collected detailed information on all activities (e.g., posts, comments, type of posts, and the timestamp of the posts) from these 31 car manufacturers’ official Facebook pages over a period of 66 months (2009.5 to 2014.10). As a result, our data includes 61252 firm-generated posts and 856749 user-generated posts. Regarding customer engagement data associated with firm-generated posts (i.e., likes, comments, and shares), our observations cover 147776669 likes, 4304106 comments, and 11406892 shares. For customer engagement data associated with user-generated posts, our dataset includes 20020511 likes, 1748393 comments, and 157077 shares between May 2009 and October 2014. We aggregated the data at the monthly level and constructed a panel dataset containing each firm’s monthly social media activates and consumers’ monthly responses. Please note that we do not use daily or weekly data because (1) the variation of firm’s social media activities at both levels was relatively small, and more importantly (2) offline car sale data from the WardsAuto Premium database is only available at the monthly level. Given the fact that not all car companies initiated their Facebook pages at the same time, our final panel contains total 1862 firm-month observations.

#### PVAR model specification and estimation procedure

We used PVAR (Panel Vector Autoregressive models) to examine the dynamics of the interactions between FGC, UGC, and offline car sales. As in traditional VAR, PVAR allows us to treat all major variables as endogenous, but PVAR also allows estimation for multiple cross sections of data, which is not available in traditional VAR (Dewan and Ramaprasad 2014). The panel nature of the data allows us to handle unobserved individual heterogeneity, while treating all variables as endogenous (Love and Zicchino 2006). Our PVAR model is specified (for both post and type of post levels) as follows:
where \( y_{i,t} = (\text{Sale}_{i,t}, \text{FGC}_{i,t}, \text{UGC}_{i,t})' \) is a three-element column vector for each car make \( i \) at time \( t \), containing the log and Helmert transformation of the dependent variable; \( \phi_s \) are 3x3 matrices of slope coefficients for endogenous variables; \( p \) is the number of lags; Trad \( i,t-s \) is the log and Helmert transformation of the monthly expenditure on traditional channel promotions by car make \( i \) at time \( t \); GoogleTrends \( i,t-s \) is the log and Helmert transformation of the monthly Google search index for car make \( i \) at time \( t-s \); Gasoline \( t-s \) is the log and Helmert transformation of the monthly gasoline price index at time \( t-s \); Consumer \( t-s \) is the log and Helmert transformation of the monthly consumer confidence index at time \( t-s \); S&P500 \( t-s \) is the log and Helmert transformation of the monthly S&P 500 return index; and \( \varepsilon_{i,t} = (\varepsilon_{1,i,t}, \varepsilon_{2,i,t}, \varepsilon_{3,i,t})' \) is a three-element vector of errors.

We followed the standard steps to conduct our PVAR analysis. In a first step, we conducted two different types of root tests to verify the absence of unit roots in our unbalanced panel data: Fisher-Type (Choi 2001) and Im-Pesaran-Shin (Im et al. 2003). The results of both tests indicate that there is no unit root in our panel. After that, we determined the appropriate lag length \( K \) using Akaike’s information criterion (AIC), following the standard approach in the VAR literature (see Holtz-Eakin et al. 1988; Love and Zicchino 2006). Specifically, we calculated AIC for each cross section and took the modal value of the optimal lag length among all cross sections as suggested by Dewan and Ramaprasad (2014). The result indicates that the lag length of 1 is the most optimal in our study. We performed two transformations to the main variables. First, we took the natural log of FGC, UGC (post-level and type of post-level), offline car sales, and traditional media advertising expenditure. As these variables have very different means and standard deviations, the log transformation is used to improve model fit (Chen et al. 2015). Since FGC and UGC (post-level and type of post-level; see Table 1) have zero observations, we added 1 to them before the log transformation. In order to remove individual fixed effects that might affect our relationship of interest (e.g., car quality), we performed the Helmert transformation on both endogenous and exogenous variables following Arellano and Bover (1995) and Love and Zicchino (2006). This transformation ensures orthogonality between the forward-differenced variables and their lagged values (Love and Zicchino 2006). Therefore, to address the issue of simultaneity, the lagged regressors are used as instruments for the forward-differenced variables and the system GMM estimator is used to allow for error correlation across equations (Dewan and Ramaprasad 2014).

**Results**

Summary statistics is presented in Table 1. Please note that we do not report data related to Facebook features (i.e., likes, comments, and shares) and five exogenous variables here to save space. Sales refer to the total number of offline car sales made by one car make in month \( t \); FGC_Post refers to the total number of posts by one car make in month \( t \); FGC_Link refers to the total number of link posts by one car make in month \( t \); UGC_Post refers to the total number of posts by users at one car make’s Facebook page in month \( t \); UGC_Link refers to the total number of link posts by users at one car make’s Facebook page in month \( t \) and so on.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
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<td>57462.24</td>
<td>97</td>
<td>284694</td>
</tr>
<tr>
<td>FGC_Post</td>
<td>32.9</td>
<td>34.11</td>
<td>0</td>
<td>1042</td>
</tr>
<tr>
<td>FGC_Link</td>
<td>6.59</td>
<td>8.67</td>
<td>0</td>
<td>62</td>
</tr>
<tr>
<td>FGC_Photo</td>
<td>20.24</td>
<td>32.45</td>
<td>0</td>
<td>973</td>
</tr>
<tr>
<td>FGC_Status</td>
<td>2.53</td>
<td>5.92</td>
<td>0</td>
<td>74</td>
</tr>
<tr>
<td>FGC_Video</td>
<td>3.12</td>
<td>3.32</td>
<td>0</td>
<td>20</td>
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<tr>
<td>UGC_Post</td>
<td>460.1</td>
<td>551.49</td>
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<td>UGC_Link</td>
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<td>UGC_Photo</td>
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<td>UGC_Status</td>
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<td>367.6</td>
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<tr>
<td>UGC_Video</td>
<td>15.79</td>
<td>22.3</td>
<td>0</td>
<td>411</td>
</tr>
</tbody>
</table>

**Table 1. Descriptive Statistics**

We first examine the results at the post-level and then the results at the type of post-level. Table 2 shows the estimation results at the post-level. When the offline car sale is the dependent variable, the coefficient estimate on
F_Posts at lag 1 is positive (.044) and statistically significant at the 0.1% level, supporting H1. On the contrary, H2 is not supported with the insignificant coefficient on U_Posts at lag 1. Next, we turn our attention to H3 to H6. The results indicate that offline car sales at lag 1 are positively associated with the volume of FGC, supporting H3. However, we did not find the support on the effect of offline car sales at lag 1 on the volume of UGC, rejecting H4. The results also show that the volume of FGC at lag 1 has a short-term positive relationship with the volume of UGC, supporting H5. Surprisingly, the volume of UGC at lag 1 is not positively associated with the volume of FGC, rejecting H6.

The results, particularly on the effect of UGC on sales, contradict most of existing literature. We, therefore, took a step further to examine whether different information representation formats (i.e., link, photo, status, and video) matter in influencing people’s decision-makings (e.g., purchase a car or post at the firm-initiated page in our context) and how. Accordingly, we examined the dynamics of UGC, FGC, and offline car sales at the type of post-level. Table 3 shows the estimation results at the link post-level. H1 is supported, suggesting that firm-generated links at lag 1 positively influence offline car sales. User-generated links at lag 1 do not influence offline car sales, rejecting H2. H3 is not supported, suggesting that offline car sales at lag 1 are not positively associated with the volume of firm-generated links. Consistently, H4 is also not supported. H5 and H6 are both supported at the link post-level, suggesting there is a positive feedback effect between firm-generated and user-generated links.

Table 4 shows the estimation results at the photo post-level. At the photo post-level, all hypotheses are supported except H2, suggesting that the volume of user-generated photos at lag 1 is not effective to influence offline car sales. Table 5 shows the estimation results at the status post-level. Only H5 is marginally supported, suggesting that posting status at the firm-initiated Facebook page is not effective in terms of increasing offline car sales and triggering customer engagement. Table 6 shows the estimation results at the video post-level. H1 and H2 are supported and firm-generated videos at lag 1 have a stronger impact on offline car sales than user-generated videos do. Offline car sales at lag 1 are not positively associated with the volume of firm-generated videos, rejecting H3. However, H4 is supported, indicating that the more offline car sales at lag 1, the more user-generated videos. Finally, H5 and H6 are both supported, suggesting that there is a positive feedback effect between firm-generated and user-generated videos.

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Dependent Variable</th>
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<tr>
<td>Sales_{i,t-1}</td>
<td>F_Post_{i,t}</td>
</tr>
<tr>
<td>.47*** (.027)</td>
<td>.21*** (.06)</td>
</tr>
<tr>
<td>F_Post_{i,t-1}</td>
<td>.044*** (.001)</td>
</tr>
<tr>
<td>U_Post_{i,t-1}</td>
<td>-.008 (.007)</td>
</tr>
<tr>
<td>Traditional Media_{i,t-1}</td>
<td>.13*** (.02)</td>
</tr>
<tr>
<td>Google Trends_{i,t-1}</td>
<td>.003*** (.0006)</td>
</tr>
<tr>
<td>Gasoline Price_{i,t-1}</td>
<td>.056** (.019)</td>
</tr>
<tr>
<td>CCI_{i,t-1}</td>
<td>.001* (.0007)</td>
</tr>
<tr>
<td>S&amp;P500_{i,t-1}</td>
<td>.0003*** (.0005)</td>
</tr>
</tbody>
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Table 2. Post-Level PVAR Regression Results
Notes: numbers in parentheses are standard errors; + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

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<thead>
<tr>
<th>Independent Variable</th>
<th>Dependent Variable</th>
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<td>F_Link_{i,t}</td>
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<td>.48*** (.027)</td>
<td>-.053 (.073)</td>
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<td>F_Link_{i,t-1}</td>
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<td>U_Link_{i,t-1}</td>
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<td>Traditional Media_{i,t-1}</td>
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<td>Google Trends_{i,t-1}</td>
<td>.002*** (.0006)</td>
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<td>.001* (.0007)</td>
</tr>
<tr>
<td>S&amp;P500_{i,t-1}</td>
<td>.0002*** (.00005)</td>
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Table 3. Link Post-Level PVAR Regression Results

<table>
<thead>
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<th>Independent Variable</th>
<th>Dependent Variable</th>
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<td>Sales_{i,t-1}</td>
<td>F_Photos_{i,t}</td>
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<td>.47*** (.028)</td>
<td>.42*** (.09)</td>
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### Conclusion and Future Plans

The objective of this research-in-progress is to assess the dynamic interactions between FGC, UGC, and offline car sales in the U.S. automobile industry. Our research context is the firm-initiated Facebook page. We collected detailed data including the official Facebook pages of 31 car companies in the U.S., and supplemented the data from these firms’ traditional media efforts, and offline car sales from 2009 to 2014. We employed PVAR to conduct our analyses at the post-level and type of post-level. Our results at the post-level indicate that FGC at lag 1 does positively influence offline car sales. However, in the setting of the firm-initiated Facebook page, UGC at lag 1 does not have the impact on offline car sales, which contradicts most of existing literature. For example, Chevalier and Mayzlin (2006) examine the effect of consumer reviews on relative sales of books at Amazon.com and Barnesandnoble.com and find that an improvement in a book’s reviews leads to an increase in relative sales at that side. The explanations of this contradicted result could relate to the nature of the product and the sites. Compared to products (e.g., book, DVD, movie, or music) that have been examined in the literature, the car is a durable goods. Therefore, customers may need to invest additional effort (e.g., test drive) before making their purchase decisions. In addition, the nature of the sites may also matter. The review site such as Amazon.com provides an environment for current and potential users to share their use experience. On the other hand, the car make’s Facebook page provides an environment to allow their fans to express their loyalty, receive the latest information from the firm, and interact with other people who share the common interests. Therefore, the Facebook page is not simply a review site. Given the nature of different sites, the volume of UGC, which is a common measure in the current literature, may have the different effect. Our results also indicate that offline car sales increase the firms’ appreciations on their Facebook pages by disseminating information more actively to engage with more customers. Finally, the current study also suggests that different information formations (i.e., link, photo, status, and video) do matter in increasing offline car sales.
sales and triggering customer engagement. Again, due to the nature of the car, customers are more likely to rely on a certain type of the format (e.g., UGC in the form of the video) for their decision-makings.

To the best of our knowledge, our study is the first academic study that rigorously examines and quantifies the effect of social media marketing in the form of FGC and UGC on offline sales over a long period of time at the industry level. In addition, our study is also the most comprehensive one by considering each possible effect of Facebook features on offline product sales (e.g., posts, content of posts, shares). Prior research on social media has focused exclusively on the effect of UGC on online sales (e.g., Chen et al. 2015; Ghose and Ipeirotis 2011; Stephen and Galak 2012). There has been limited attention on the relative impacts of UGC and FGC on offline sales and their dynamics interactions. Our results provide empirical evidence that online content generated by both firms and users could have a significant effect on offline sales. Therefore, we expect to contribute to the current literature by representing a more comprehensive framework to examine the impact of social media. In addition, our study also will contribute to the existing literature by showing how different information representation formats (i.e., status, video, photo, and video) influence offline product sales and attract customers’ attention. The current study will also provide practical implications for practitioners. Given the large amount of digital and traditional media spending in the U.S. automobile industry, this study will shed light for firms to pay special attention to the content of their marketing communications and develop the most effective conversations to engage their customers.

It should note that firms have a significant presence at other social media sites, such as Twitter, Instagram, or Blogs. These social media sites have dramatically different features and activities on these sites could also affect offline car sales. Due to data limitations, we are not able to study the interactions between offline car sales and the overall marketing intensity across different social media sites. The comparison of these different social media sites could help firms better form their social media strategies. Finally, it should also note that at the time of writing not all car makes have the similar proportion of their Facebook users (i.e., the total number of people who like a car make’s Facebook page). Facebook only allows the page creators to measure the historical trend of their online user base. Therefore, we are not able to observe if the trend is consistent over time, which may represent unobserved individual heterogeneity. The panel nature of our data allows us to handle this heterogeneity using some methods such as the fixed effect. Besides, the category of the car make (e.g., luxury vs. economy) could also help us better understand how different groups of the car make leverage social media to enhance offline car sales.

Our future plans for this research-in-progress are to (1) examine customer engagement data (i.e., likes, comments, and shares) associated with FGC and UGC, (2) conduct the textual analysis using General Inquirer (a textual program developed by Harvard University) to determine positive/negative FGC and UGC and then examine their relative impacts on offline car sales, (3) illustrate the long-term behavior of the PVAR model using impulse response functions (IRF), (4) conduct subsample analyses (US-based, Asia-based, and European-based firms) to see if there is a significantly different result among these three different areas, (5) categorize car makes into different groups (e.g., luxury vs. economy) to examine if the effect could be held across different groups, and (6) if data is available, we would like to take a step further to study the interactions between offline car sales and the overall marketing intensity across different social media sites.

Appendices

Car Makes

Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, GM, Honda, Hyundai, Infiniti, Jaguar, KIA, Lexus, Mazda, Mercedes-Benz, Mitsubishi, Nissan, Porsche, Toyota, Volkswagen, Volvo, Lincoln, Subaru, Saab, FIAT, Jeep, Land Rover, Scion

Traditional Media Categories

Network TV, Spanish-language network TV, Cable TV, Syndication, Sport TV, Magazines, Sunday Magazines, Local Magazines, Hispanic Magazines, B-to-B Magazines, National Newspapers, Newspapers, Hispanic Newspapers, Network Radio, National Sport Radio, Local Radio Summary, Local Radio Historical, Outdoor Displays

References