# The Effectiveness of Promotional Events in Social Media

**[The bulk of the work was done by students]**

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## Abstract

This paper studies a pioneering social media venture and seeks to understand the effectiveness of promotional events in social media platforms by evaluating their impact on participating brands. We employ a promising research approach, based on the event study methodology, and use a rich database consisting of all the promotional events on Twitter by American Express Company and its participating partners. Based on the results of the presented econometric analysis and focusing on the long-term business value of this novel use of social media, we find that promotional events combined with implicit or explicit advocacy on social media platforms result in significant abnormal returns for the participating brand, in terms of fan base and new

followers on the social media platform. The effect is also economically significant as it corresponds to an increase of several thousand new followers for a brand of an average size. Finally, we both contribute to the related literature, discovering new rich findings, and provide actionable insights with major implications for brands, marketers, and social media platforms. One of the factors affecting significantly the results of promotional events is the timing of announcing the promotion and broadcasting the corresponding brand message on social networks. Brands and marketers should post ads and promotions on social networks during the time of peak usage in order to maximize their returns.

**Keywords:** Business Analytics, Event Study, Observational, Counterfactual, Econometrics, Social Media, Online Social Networks, Business Value, Social Commerce, User base

# Introduction

Social media are fundamentally changing the way we communicate, collaborate, and consume. They represent one of the most transformative impacts of information technology on business (Aral et al. 2013) as they drastically change how consumers and firms interact. Harnessing the opportunities social media generate, marketers nowadays are seeking better ways to create or further increase the consumers' connection and engagement with their brand. As consumers spend an increasing amount of their time online and the percentage of adults using social media has significantly risen over the last years, companies invest a growing amount of their marketing budget towards online and social media advertising, invent new ways to establish strong connections with their customers into the online world, and leverage their social connections. Therefore, companies nowadays increasingly compete for consumers' attention and engagement with their brand in the social media space. Content generation, nurture of positive online word-of-mouth (WOM), and utilization of social links among customers are some quintessential effective means of non-paid advertising for companies to spread their message in real time and generate leads associated with key marketing objectives.

Social commerce is a representative example of leveraging the social connections between users to generate leads for the business. The term "social commerce" was first introduced in 2005 by Yahoo! (Rubel 2006) and initially referred to a feature that allowed users to review products on the Yahoo! shopping platform. During the next years, the scope of the term "social commerce" expanded in various directions incorporating peer recommendations, shared shopping lists, product referrals, coupon sharing, team-buying (i.e., a group of customers gathering together in

order to bargain with merchants), "deal-of-the-day" websites (i.e., e-commerce websites where a minimum number of purchases should be reached in order an offer to be activated), network-based marketing and integration of online merchandisers with social network platforms, and company-controlled online communities (Wang and Zhang 2012). Towards this direction, American Express Company (Amex) recently pioneered a "social commerce" venture on the social media platform of Twitter, Inc. based on which a user can purchase a product or claim a promotional offer from a participating brand by sending a short 140-character text message, called "tweet", with a designated keyword (i.e., hashtag). The service has already been deployed in large scale offering to users credit of $15 million just in April 2014 (American Express Company 2014). The social commerce initiative of Amex on the social network of Twitter builds on concepts related to the previous social commerce ventures but also exhibits some unique features. For instance, in this setting all the transactions are by default visible to the users of the platform, each purchase and offer takes place within the platform itself using only the core feature of the platform (i.e., designated hashtags), both physical and electronic products are available, and the products and offers are delivered to the user that completed the transaction instead of other users (e.g., Facebook gifts).

The aforementioned unique features of this new venture and the simplicity in completing purchases and claiming offers generate tremendous potentials as they can fundamentally change the way consumers shop online and interact with brands. Wrapping the entire purchase process into a hashtag, the service makes the transactions fast and easy for the consumers. At the same time, the proposed service capitalizes the unique opportunity for social media to generate direct return on investment. Thus, the short-term effects of such an offering seem straightforward for

both the consumers, who save money on their purchase, and the marketers, who generate sales and buzz around their brand.

Studying the consumer behavior in this modern social commerce service, in (Todri and Adamopoulos 2014) we elucidate the factors that drive and affect the consumers' decision to adopt this novel service and make a purchase that will automatically be disclosed to the social network. In particular, employing both econometric and predictive models, we study how the characteristics of the user and her social network affect the decision to make a purchase and engage into WOM at the same time, in an attempt to better understand how firms can conduct business through social commerce and spur online conversations. Based on the empirical results, we find that various user characteristics, the brand loyalty and trust of the users, and their familiarity with the platform have significant effects on the likelihood of adoption and social purchases. Additionally, we find that the economic behavior of a user's immediate social network as well as the personalization and the valence of recommendations from the social neighbors of the user have also significant impact on her/his decisions to make such purchases. Besides, observing the WOM episodes, the breadth of their dissemination, and the valence of the recommendations, we are able to study the distinguishing characteristics of the disseminators that are associated with successful post-purchases (i.e., after the transaction of the disseminator has been broadcasted to the network) of their neighbors either due to awareness or influence effects. The derived models provide specific guidelines for marketers orchestrate WOM in social networks.

However, building on our previous work, this paper assumes the point of view of social brands and attempts to focus on the long-term effects of such social media campaigns enabled by the unique salient features of the social medium. Amex essentially turns every single purchase or offer claim into an advertisement as the social neighbors of the customer gets exposed to the public advocacy and endorsement of the brand or the product from a fellow friend. The service is an exemplary model of how a highly engaging social media campaign could generate commitment from the consumers and reinforce their loyalty to the brand. Therefore, we attempt to elucidate the role of promotional events, in conjunction with public advocacy and endorsement features, in increasing the user fan base for the participating brand. Any change in the number of followers (i.e., the user base) of a company is a visible important indicator of firm performance, since a user following a brand on Twitter can be considered as implicit word-of-mouth and recommendation. Besides, companies are particularly interested into attracting more followers for their social media profiles and capitalize on every opportunity to do so as in the long-run they can more easily generate brand awareness, create engagement, and spur online WOM. Furthermore, a larger fan base might further enhance the company's ability to harness this power and effectiveness of social media (Todri and Adamopoulos 2014). According to the hierarchy of effects, such key marketing objectives are directly linked to increased sales (Tellis 2004) and it has been shown that the corresponding social media-based metrics are significant leading indicators of firm equity value (Luo et al. 2013).

In this paper, we seek to understand the long-term effectiveness of promotional events in social media platforms integrating public advocacy and endorsement features by examining their impact on the image of the participating brands, specifically their fan base. Focusing on the long-

term business value, we employ an event study methodology using a real-world data set consisting of *all* the promotional events by Amex and other participating brands on Twitter, more than 65 million brand-related tweets and detailed information for more than 2 million users. We find that promotional events combined with implicit or explicit advocacy on social media platforms result in significant abnormal returns for the participating brand, in terms of new followers. We both contribute to the related literature discovering new rich findings and provide actionable insights with implications for both marketers and social media platforms.

## Related Work and Hypotheses Development

Employing the unique hashtag feature of Twitter, American Express effectively transforms the specific social media platform into a social commerce platform, where consumers can directly buy products or claim promotions with the easiness of a tweet and automatically spread the word about the offers. This novel emergent type of e-commerce and user engagement is related to several streams of research from different fields, including Information Systems, Marketing, and Economics. These streams of research include network-based marketing, mobile coupons, real-time marketing and word-of-mouth (WOM). We review the extant literature to summarize previous work and develop our research hypotheses.

Network-based marketing refers to a collection of marketing techniques that take advantage of links between consumers to increase sales and create buzz. Different modes of network-based marketing have been identified in prior literature. For instance, "network targeting" refers to a firm marketing to prior purchasers' social-network neighbors, possibly without any action by the customers, whereas "advocacy" involves particular individuals becoming either vocal advocates

(i.e., explicit advocacy) for a product or service recommending it to their friends and acquaintances or implicit advocates through their own actions (e.g., adoption of a specific service or product) (Hill et al. 2006). In the particular setting of Twitter and Amex, consumers automatically reveal their purchases and, thus, contribute to the implicit advocacy. Consumers may additionally choose to personalize the tweet messages they share with their social neighbors and, thus, become explicit advocates. Hence, Amex and its partners using complimentary modes of network-based marketing as an integral part of the purchase process aim at taking full advantage of the social links between customers in order to drive awareness, sales, and engagement. Thus, as the customers spread the word about an offering and advocate the corresponding brand through their product endorsements, more social media users get exposed to the promoting brand and its activities and through a variety of influence processes, including those that raise awareness as well as those that persuade individuals to change their expectations (Aral 2011), might decide to become social media followers of the particular brand in order to keep up to date with the company's products, services and offerings. On the other hand, promotional events might have a negative impact since such promotions may lead to inferences about the value and quality of the brand and its products. In particular, consumers, especially those that are not familiar with the brand, might interpret these promotions as a signal that the specific product is of low quality or that the firm is in trouble (DelVecchio et al. 2006; Simonson et al. 1994). However, in the online world, thanks to the advancements of modern information systems as well as the valence and volume of online reviews, consumers have easier access to higher quality information, which in combination with the lower search costs, improves their ability to compare different brands and products (Bakos 1997) and, thus, the potential

influence of such negative signals will be reduced. Besides, because of the increased price competition and the more frequent price adjustments online (Brynjolfsson and Smith 2000) as well as the increased price sensitivity of consumers (Chevalier and Goolsbee 2003), such promotions are also less likely to be perceived as negative signals. Hence, promotional events on social media are less likely to have a negative impact. Therefore, we propose that:

> *H1: A promotional event combined with features of implicit and/or explicit advocacy is likely to attract new followers for the participating brand.*

Besides, the current fan base of a brand might affect the potential of promotional events on social media to attract new followers through online WOM. Research suggests that both volume and valence of WOM have a significant impact (Chevalier and Mayzlin 2006) while some prior empirical studies indicate that the volume of WOM is more effective than the valence through the awareness effect (Liu 2006). Especially in online social media and networks, the large number of users offers the potential for online WOM at much larger scale, causing online social networks to render online WOM more convenient than traditional WOM (Dellarocas 2003; Zhu and Zhang 2010). Since new customer acquisition is crucial for businesses and given the aforementioned importance of social networks, social media platforms have attracted the attention of many companies who have a perennial interest in leveraging social relationships to extend their customer base (Shi et al. 2013). Nonetheless, the current network fan base could either amplify or attenuate the effectiveness of promotional events on attracting new followers. For instance, despite the awareness effect of such promotions, it might be more difficult for a company with a larger existing fan base to attract new fans due to saturation effects since it is more likely for a

user to have already made a conscious decision in the past whether to follow the particular brand or not. On the other hand, a large fan base might positively affect customers' decision to follow a brand through a social influence bias (Muchnik et al. 2013) contributing to a "rich-get-richer" effect. Therefore, we hypothesize that:

> *H2a: A promotional event from a brand with a smaller existing fan base is less likely to attract more followers for the participating brand.*

> *H2b: A promotional event from a brand with a smaller existing fan base is more likely to attract more followers for the participating brand.*

Moreover, Twitter as a social medium is closely aligned with the trends towards mobile (Balasubramanian et al. 2002) and real-time marketing. Twitter is currently one of the few social platforms that has already captured the "in-the-moment" context and this allows marketers not only to propagate their messages in a timely manner but also to capitalize the context and the mindset in which the consumer is more likely to be receptive and responsive to an advertiser's message (Williamson 2014). Hence, advertisers who would like to embrace the real-time opportunities of Twitter would be interested into choosing the correct time of promoting such events on the Twitter platform in order to maximize the return on engagement/investment. In particular, someone might argue that the time of peak usage would increase the chances of exposure to a greater audience and thus would attract more followers. However, it could be also the case that at the time of peak usage propagating a promotional message is very competitive and so less effective in attracting consumers' engagement and attention. Therefore, we hypothesize the following:

*H3a: A promotional event that is announced at the time of peak usage of the social media platform is more likely to attract more followers for the participating brand.*

*H3b: A promotional event that is announced at the time of peak usage of the social media platform is less likely to attract more followers for the participating brand.*

Furthermore, the ability of a marketer to attract new followers will depend on the perceived benefits of the promotional event as well as the expectations users form about future events. Dickinger and Kleijnen (2008) investigate consumers' intentions to redeem mobile coupons since coupon redemption rates are important drivers of sale increases, profits, and market performance (Leone and Srinivasan 1996; Raghubir 2004). They suggest that the economic benefit is a significant determinant of the coupon usefulness and attractiveness and, consequently, we theorize that in a social commerce setting a promotional event with a larger percentage discount is more likely to attract more followers for the participating brand. Besides, the ability to claim an offer multiple times allows for additional monetary savings and would be likely to generate more followers who benefit from accumulated savings. Therefore, a promotional event with an offer that can be claimed multiple times by a single customer is more likely to attract more followers for the participating firm. While higher savings would be likely to attract more followers, the minimum required amount a customer is required to spend also comes into play. Hence, a promotional event requiring a larger amount (USD) of minimum spend is less likely to attract more followers for the participating brand. Additionally, Molitor et al. (2012) show that the closer the consumers are to the physical store offering the coupon, the more likely they are to download the mobile coupons. Thus, in a social commerce setting, a

promotional event that is valid only in brick-and-mortar store and not online is hypothesized to be less likely to attract more followers for the participating brand. Based on the above discussion, *a promotional event with higher expected benefit is more likely to attract more followers for the brand and hence we measure the corresponding effects*.

As far as the methodological framework employed in this paper is considered, event studies represent a relatively new but promising research approach which looks at abnormal returns and reactions to specific events or happenings and measures directly the changes in the quantity of interest. Events studies have been widely used in economic and finance research where they provide a powerful setting to examine the informativeness and impact of an event, such as investments and acquisitions, on the stock price of a firm. However, at their most general level, event studies do not necessarily include or require stock market information. Instead, there could be a relationship between an event and *any* dependent variable. Thus, the applicability of event studies is not limited to economic and financial research. Nevertheless, in Information Systems (IS) research, event studies have become reasonably popular only during the last ten years or so. Since then, they have been used, for example, to identify specific factors that influence the outcomes of information technology (IT) investments by publicly traded firms. Nonetheless, in recent years, the focus has been extended beyond IT investments to other issues, such as security incidents, IT outsourcing initiatives, e-commerce investments, and standardization projects (Roztocki and Weistroffer 2009). Comparing event studies with other methodologies for estimating average treatment effects, such as the difference-in-differences method or model free approaches, event studies are not limited to only two time periods (i.e., pre-intervention and post-intervention), they do not assume that the event (or treatment) is exactly the same for

all treated members, that it has the same effect in every time period, nor that it is static and has no duration, but event studies can include flexible leads and lags. Besides, among other differences, event studies do not necessarily need control groups that consist of the same untreated individual members over time and hence do not suffer from a possible violation of the parallel trend assumption, even though event studies are flexible enough and can include such control groups or "market" observations if preferable.

## The Business Model and Data Generating Process

The data generating process of the specific social commerce case we study differs significantly from traditional online commerce. In particular, American Express announces the list of participating brands and the corresponding promotional sales and offers with their respective terms. The featured promotional products and offers belong to a wide variety of categories, including retail, travel, entertainment, etc. A typical announcement for such a promotional offer is the following: "*Tweet #AmexDell, get $100 back 1x on next $599+ online purch w/synced Amex Card! QtyLtd, Exp 4/30. Terms http://aexp.co/RGr*". Respectively, a typical promotional sale announcement is the following: "*Get Xbox 360 4GB for $179.99+tax w/synced Amex Card. Tweet #BuyXbox360Bundle to start purchase! QtyLtd Exp 3/3 Terms http://amex.co/W4X7xa*". Consumers who are interested into making a purchase or claiming an offer must have a Twitter account and sync their Amex account with Twitter through an easy opt-in process. Hence, only Amex cardholders and Twitter users are eligible to participate in the program. Once Amex announces the offers, users can purchase the products or claim the offers by posting a tweet (a message of maximum 140 characters) with the designated hashtag or by re-tweeting the specific

announcement. Such a tweet is publicly posted on the Twitter profile of the user (private accounts were not eligible to participate in the program) and her/his social network friends will automatically receive the tweet on their own timelines. Amex tracks these tweets that use the designated hashtag in the social network and matches them to the desired product or offer. After the tweet is automatically processed, a reply is sent to the user verifying the terms of the offer or asking to confirm the purchase within fifteen minutes. In the case of a product purchase, once the transaction is confirmed by the user within the designated timeframe, Amex bills the customers or credits the promotional amount in a following eligible purchase, respectively. We should not that a user is not required to follow neither Amex nor the participating brand in order to purchase a product or claim an offer.

Our data set contains *all* the promotional events available by Amex and the participating brands on Twitter. For each promotional event, the available information in our database and the derived variables include, among others, the percentage discount of the promotional event, the minimum amount a user is required to spend in order to be eligible for the promotion, whether the promotion is available only for in-store purchases, whether the promotional event corresponds to a product purchase or a discount offer, whether the promotion can be claimed multiple times from a single user, the number of followers of the participating brand when the announcement of the promotional event was sent, and whether the offer was announced between 12:00pm and 4:00pm, which is the peak of user activity on Twitter platform (Zarrella 2009). The data span all the promotional offers and sales that took place since the program was launched, March 2012, using the automated handle @AmexOffers until the end of March 2014. Table 1 summarizes all the variables related to the promotional events, which were used in the

analysis, and shows the corresponding descriptive statistics computed over all the observations

in our data set.

| Table 1. Variables and Descriptive Statistics | | | | | |
|---|---|---|---|---|---|
| **Variable** | **Description** | **Mean** | **Std. Dev** | **Min** | **Max** |
| # Followers | The number of followers of the participating brand on Twitter | 125,658.6 | 389,098.7 | 952 | 6,864,324 |
| % Discount | The promotional discount | .2487 | .1700 | .1 | 1 |
| $ Minimum Price | The minimum amount (USD) a user is required to spend to be eligible for the promotion | 126.61 | 213.10 | 0 | 2,500 |
| In-Store Purchase | Whether the promotion is available only for in-store purchases | .6684 | .4708 | 0 | 1 |
| Pay-By-Tweet | Whether a user can purchase the promotional product using the 'Pay-By-Tweet' service | .0320 | .1664 | 0 | 1 |
| Unlimited Use | Whether the promotion can be claimed multiple times from a single user | .0285 | .1664 | 0 | 1 |
| Social Network Peak Time | Whether the promotion was initially announced between 12:00pm and 4:00pm | .3656 | .4816 | 0 | 1 |

Additionally, using the Twitter API we have access to the daily number of followers, friends, and

statuses, since 2011 (or the date the account was created and verified by Twitter) and for each

calendar day, for all the verified accounts on Twitter and all the official brand accounts. Finally,

for each brand we have also collected the corresponding economic and market sectors in which it operates as well as their user social network. In summary, we have data on 272 promotional events from 179 brands as well as daily observations for more than 20,000 brands across various industries.

## Event Model and Empirical Analysis

In economic research, an event study first requires identifying the event of interest (e.g., announcement of a merger between two business entities). After the event is defined, the period of time over which the corresponding quantity of interest (e.g., stock price of the firm) is adjusted is determined. Then, the quantity of interest is observed and the changes in response to the event, beyond the "normal" or expected level in the absence of the event, are examined to determine the extent to which the event changes the quantity of interest (Konchitchki and O'Leary 2011). Nevertheless, event studies are not limited to economic and finance research and do not necessarily include or require stock market information but there could be any relationship between an event and a dependent variable, without the need to presume market efficiency as in stock market studies; however, the motivation and the theories used to generate expectations are likely to differ across disciplines (Konchitchki and O'Leary 2011). In such settings, event studies can be a superior framework to various alternative approaches in investigating the response to particular happenings. MacKinlay (1997) outlined an event study methodology involving the following steps: (i) identification of the *event of interest*; (ii) definition of the *event window*; (iii) selection of the *sample* set of firms to be included in the analysis; (iv) prediction of the *"normal" return* during the event window in the absence of the event; (v) estimation of the

*"abnormal" return* within the event window, where the abnormal return is defined as the difference between the actual and predicted returns without the event occurring; and (vi) testing whether the abnormal return is statistically different from zero.

In the particular setting of social commerce, participating firms and American Express make announcements on Twitter about specific promotions. Such announcements serve to inform the users about the corresponding terms of each promotion and, for this study, they constitute the events of interest. If the promotion is attractive to social media users, a positive response to this promotion is expected from their side. In the short-run, the company benefits from the generation of sale leads and the buzz created around its brand. A central tenet of our approach though is that in the long-run this potential positive response can be translated into an abnormal increase of the user base of the participating brand. On the other hand, if the promotion is unattractive to the users, a negative impact on the user base can occur.

The "*event window*" indicates the number of days before and after the announcement date over which the abnormal returns are accumulated. An event window is typically denoted $(-x, +y)$, where $x$ is the number of days before the announcement day and y is the number of days afterwards, while the announcement day is typically denoted as "day 0". Including days before the announcement captures information leaks, either from the press or internal users (Konchitchki and O'Leary 2011). In order to capture such information leaks in this setting of social commerce, we consider as the starting point of the event window for each promotional event the earliest time of the actual announcement of the promotion or the first message claiming the specific offer, if information leakage occurred; in some cases the first response to a promotion is

observed a few hours before the actual announcement of the promotion because of information leakage via the employees of Amex or the participating companies. Besides, we narrow the width of the event window to five days refining the effect as precisely as possible and accurately estimating -a lower bound of- the causal impact of the event. This design choice is common in various settings and is motivated by the potential presence of confounding effects over a wide event window. The use of shorter windows reduces the potential for a confounding event to interfere as well as limits the impact of other events on the event of concern. If the event under study affects the dependent variable for a longer period than the selected event window and in the absence of confounding effects after the selected event window and during the influence of the particular event, we underestimate the total causal impact of the event but the results can still be interpreted as the causal impact of the event during the $x + y$ first days or more generally as a lower bound of the causal effect. These design choices are also consistent with the suggestions of Konchitchki and O'Leary (2011) for effectively designing event studies in information systems research.

Then, the *sample of firms* is chosen based on the particular event of interest. The set of candidate firms consists of all the participants that had a promotional event on Twitter. The final sample though includes only the firms for which a confounding effect was not observed during the event window or the estimation window for the observations used in estimating normal returns. For instance, one of the candidate firms announced a promotion during the time period when it sponsored a major festival and thus we excluded the firm from the final sample, since the change in the dependent variable could not be untangled from the confounding event and attributed to the particular promotion. Eliminating such announcements that may be tainted by another event

or a set of events is an important step towards precisely estimating the causal effect of an event. The confounding events during both the event window and the estimation window were independently identified by two appointed graduate students and correspond to a small number of observations.

Besides, the significance of the impact of the event during the event window is usually assessed relative to what is referred to as the *estimation window* (or normal return period) over which a model of the normal returns as well as the variance of abnormal returns are estimated. The observations used to learn the model of normal returns for the counterfactual market response correspond to the specific brand and/or a set of similar companies, the control group, and other predictor variables; the specific set of control time series is described in detail in the following paragraphs. The model learned during the estimation window is used to predict normal returns over the event window (i.e., expected returns at the absence of the event), which are then compared to the abnormal returns. The length of the estimation window is selected to be 120 days, ending immediately prior to the event window.

After estimating both the normal and abnormal (i.e., actual) returns over the event window, we focus on examining the cumulative abnormal return as follows:

$$CAR_i = \sum_{t=-x}^{+y} AR_{it}$$

where $AR_{it} = R_{it} - E(R_{it})$ is the point-wise difference between the actual observed outcome and the predicted counterfactual at the absence of an intervention, $R_{it}$ the actual return of firm $i$ on day $t$, $E(R_{it})$ the corresponding expected return for the same firm and day at the absence

of the event (i.e., based on the model learned during the estimation window), and $t \in (-x, y)$.

In particular, the model of normal (expected) returns for each firm is

$$R_{it} = y_{it} = a_i + \boldsymbol{\beta}_i \boldsymbol{x}_{it} + \gamma_i^b \sum_{j \in B} w_{jt}^b + \gamma_i^f \sum_{j \in F} w_{jt}^f + \gamma_i^s \sum_{j \in S} w_{jt}^s + \delta_i s_{it} + \zeta_i z_t$$

where $y_{it}$ is the natural logarithm of the ratio of number of followers in day $t$ over the number

of followers the previous day, $\boldsymbol{x}_{it}$ is a vector that contains dummy variables about the day of the

week and whether there was a bank holiday, $w_{jt}^b$ is the natural logarithm of the ratio of number

of followers of brand $j$ in day $t$ over the number of followers at $t-1$ for $B$ verified on the social

network firms, $w_{jt}^f$ is correspondingly the logarithm of the ratio of followers for $F$ similar firms

(based on common followers), $w_{jt}^s$ is the same metric for $S$ similar firms (based that belong to the

same industry and economic sector), $s_{it}$ the number of statuses (messages) posted on the social

network by brand $i$ at time period $t$, and $z_t$ captures any time trend of the change in

performance. These models are then used to predict normal performance during the event

window. The aforementioned predictor timelines and the corresponding control firms of each

brand included in the above model were selected based on i) all the officially verified accounts

on the social network that correspond to a brand, ii) the relative number of common Twitter

followers using the Jaccard coefficient and setting $F = 10$, and iii) all the verified firm account

which belong to the same industry and economic sector. The use of the specific formulation of

the dependent variable allows the comparison of results across brands and better fits the large

range of the quantity of interest; alternative formulations are discussed as robustness checks.

Figure 1 shows for a specific firm the observed time series and the predicted counterfactual, the abnormal returns per time period, and the cumulative abnormal returns. For illustrative purposes, in Figure 2 we use as dependent variable the number of followers and show the effect for the same brand and promotional event.
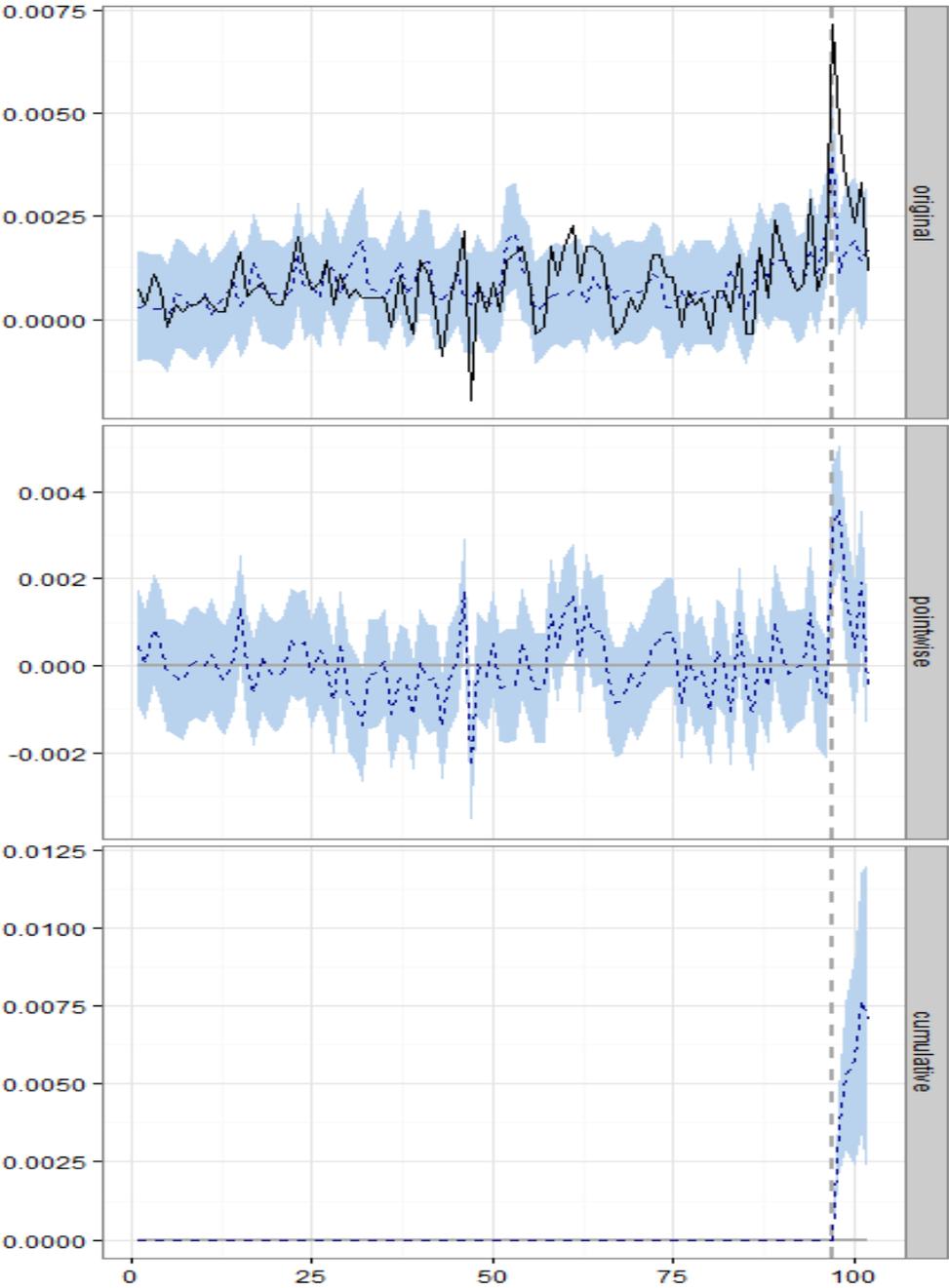


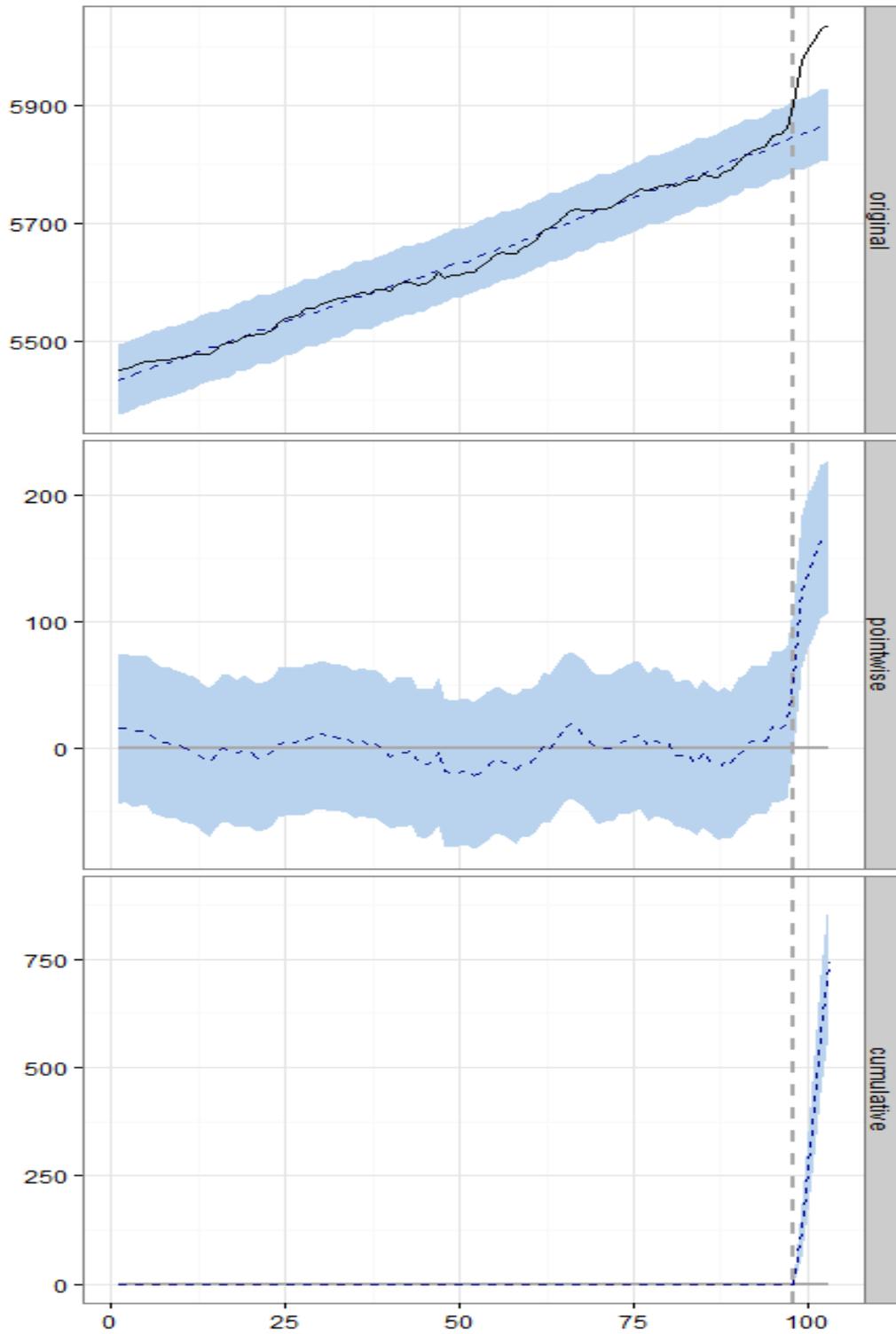*Figure 1: Effect of a promotional event on number of followers.*

*Figure 2: Effect of a promotional event on number of followers.*

The statistical significance of the abnormal returns ($AR_{it}$) as well as the cumulative abnormal returns ($CAR_i$) can be tested using the corresponding $t$-statistics and the corresponding sample standard deviation in a time-series approach taking into account also any cross-sectional dependence. Thanks to the narrow event window, the test-statistic is not very sensitive to the benchmark model of abnormal returns or assumptions about cross-sectional or time-series dependence of abnormal returns (Konchitchki and O'Leary 2011). Additionally, the significance of the cumulative abnormal returns for all brands as a group can also be estimated.

Finally, we also conduct a complementary analysis investigating any potential differences in the estimated (cumulative) abnormal returns of the various firms. In particular, we explain the differences in the magnitudes of the returns across brands in terms of event characteristics using the following model:

$$CAR_i = y_i = \alpha + \boldsymbol{\beta x}_i + \gamma w_i$$

where $\boldsymbol{x}_i$ a vector of the relevant characteristics of the promotion, including the promotional discount, the minimum amount (USD) a user is required to spend to be eligible for the promotion, whether the promotion is available only for in-store purchases, if the promotion can be claimed multiple times from a single user, and whether the promotion was announced between 12:00pm and 4:00pm, which is the peak of user activity on Twitter platform (Zarrella 2009), and $w_i$ the initial size of the brand fan base at the time of announcement of the promotion.

## Results

After learning the model of normal returns for each brand taking into consideration the observations about the brand itself before the treatment as well the behavior of a set of other

time series that were predictive of the target prior to the intervention and based on their values on the post-treatment period, we computed the daily abnormal returns and the cumulative abnormal returns for each firm. The daily abnormal returns are computed by subtracting the predicted normal return from the actual return for each day in the event window. Then, the cumulative abnormal returns are measured as the sum of the abnormal returns over the event window. As Table 2 shows, the cumulative abnormal returns are positive and statistically significant and thus provide support for the hypothesis that brands which participate in promotional events with explicit and/or implicit advocacy are more likely to attract more followers and expand their fan base (*H1*), illustrating the long-term effects of such promotional events on social media platforms.

| Table 2. Cumulative Abnormal Returns Across All Events | | | |
|---|---|---|---|
| **Variable** | **Coefficient** | **Robust Std. Err.** | **t-statistic** |
| Cumulative Abnormal Returns | .0019596 *** | .0005813 | 3.37 |

Robust standard error are reported

 **\*** significant at 10%; **\*\*** significant at 5%; **\*\*\*** significant at 1%

The identified effect is also economically significant as it corresponds to an increase of about 5,000 thousand new followers for a brand of an average size. Then, as described in the previous section, we also conducted a complementary analysis investigating the differences in the estimated (cumulative) abnormal returns of the various brands and promotional events.

| Table 3. Model of Abnormal Returns | | | |
|---|---|---|---|
| **Variable** | **Coefficient** | **Robust Std. Err.** | **t-statistic** |
| Constant | .0059222 *** | .0014266 | 4.15 |

| | | | |
|---|---|---|---|
| % Discount | .0005139 *** | .0000849 | 6.05 |
| $ Min. Price | -3.70e-06 ** | 1.25e-06 | -2.95 |
| In-store Purchase | -.0075032 *** | .0016533 | -4.54 |
| Unlimited Use | .0011744 | .0009001 | 1.30 |
| Pay-By-Tweet | -.0104336 *** | .0023861 | -4.37 |
| Initial Brand Followers | .0000148 ** | 5.55e-06 | 2.67 |
| Social Network Peak Time | .0041712 ** | .0013765 | 3.03 |

Robust standard error are reported

**\*** significant at 10%; **\*\*** significant at 5%; **\*\*\*** significant at 1%

Based on the results presented in Table 3, a promotional event from a brand with a smaller existing fan base is less likely to attract more followers for the participating brand (*H2a*). Besides, a promotion that is announced at the time of peak usage of the social media platform (*H3a*) is more likely to attract more followers for the participating brand. Consistent with prior literature, a promotional event with a larger percentage discount and a smaller required amount as minimum spend is more effective. Additionally, a promotion that is valid online, corresponds to a discount offer and not a specific product purchase, or can be claimed multiple times by a customer is more likely to attract more followers. Thus, a promotional event with higher expected benefit is more likely to attract more followers for the brand.

## Robustness Tests

Additionally, as robustness checks, we used different dependent variables, such as the percentage change in the number of followers or the number of (new) followers for each day, and different numbers $(B, F, S)$ of similar brands as controls (e.g., 5, …, 50). Besides, in order to assess the effect of potentially over-fitting our data, we also estimated the models using only the

performance of brands that belong to the same industry and economic sector or just their average performance, instead of the extended set of control time series that we employed in our main analysis. Similarly, we also evaluated the effect using only similar brands based on the Jaccard coefficient computed using the set of followers of each brand. Furthermore, similar results were observed on average by learning either a pooled model of normal performance for all the firms and allowing for firm-specific fixed effects or brand-specific models. Finally, various extra robustness checks were conducted, by varying the length of the event and estimation windows, corroborating qualitatively our findings.

## Falsification Checks

One might think that it is plausible that the previous set of models are simply picking up spurious effects as a result of pure coincidence, a general increase in the corresponding metrics, or other unobserved factors. To assess the possibility that the aforementioned findings are a statistical artifact and the identified positive significant effects were captured by chance or because of other confounding factors, we run a falsification tests using the same models (in order to maintain consistency) but randomly indicating when each promotional event took place. In particular, we use a standard (pseudo) random number generator in order to create a dummy variable that indicates when each promotional event occurred; when drawing the pseudo event day always we allow for an estimation window at least 30 days long and a (pseudo) event window that immediately follows this estimation window and does not overlap with the actual event window of the real event.

Under this falsification test, since the pseudo event window was not affected by the events of interest, the corresponding variable of interest of abnormal returns should not pick any effect in the falsification models and show that there is no impact. The results of these falsification tests are shown in Table 4. We see that, under this check, the corresponding cumulative abnormal returns are negative and not statistically significant, indicating that our findings are not a statistical artifact of our specification, but we indeed discovered the actual effects.

| Table 4. Falsification Check | | | |
|---|---|---|---|
| Variable | Coefficient | Robust Std. Err. | t-statistic |
| Cumulative Abnormal Returns | -.0007863 | .0004943 | -1.59 |

Robust standard error are reported

 * significant at 10%; ** significant at 5%; *** significant at 1%

# Conclusion

Studying the pioneering social media venture of American Express on the social network of Twitter, we both contribute to the related literature in social media and marketing, discovering new rich findings, and provide actionable insights with implications for network-based targeting, social media marketing, and social media platform design. The current paper, extends our prior work on social commerce that examined the consumer behavior in modern social commerce (Todri and Adamopoulos 2014). In this study, we focus on the long-term business value of this novel use and application of social media and we find that promotional events combined with features enabling implicit or explicit advocacy on social media platforms result in statistically significant positive abnormal returns, in terms of new followers for the corresponding brands. In particular, we identify an effective method for brands to attract more followers and expand their

social media fan base, which they can later leverage in order to increase awareness, engagement, and word-of-mouth (Todri and Adamopoulos 2014). Besides, we illustrate that promotional events on social media are more effective for brands that already have a large user base, since they can more effectively propagate their messages; this might contribute to a "rich get richer" effect on social media. Moreover, we show empirically when consumers are more receptive to such promotional events on social media and thus suggest specific tactical strategies for firms that would like to capitalize on the real time marketing feature of the Twitter social network. Towards this direction, we precisely quantify the impact of the various promotion characteristics and demonstrate what types of promotions are effective for generating desired long-term effects. We discover that the most important factor in increasing significantly the returns of promotional events is the timing of announcing the promotion and broadcasting the corresponding brand message on social networks. Hence, based on the aforementioned results, one of the tactical strategies for brands and marketers is that, despite the increased competition for consumers' attention, posting ads and promotions on social networks during the time of peak usage maximizes their returns as the messages can be more widely disseminated to the network.

A limitation of this study is that selecting a narrow event window we might under-estimate the actual causal effect of the particular events. Moreover, firms that announced the promotions during other confounding events were excluded from the sample, since the effect could not be untangled from the confounding event and attributed to the particular promotion. Such firms might experience even higher abnormal returns because of synergies and complementarity effects. As part of the future work, we plan to study how the effect of promotional events evolves

over time and its decay structure as well as the impact of social media promotional events on consumers' perceptions of participating brands.

## Acknowledgments

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