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Effects of Promotions on Location-Based Social Media: Evidence from Foursquare

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ABSTRACT: Location has been identified as a critical factor for the success of a business. For example, businesses in dense urban areas are exposed to more customers than businesses in sparsely populated neighborhoods, while proximity to a popular landmark can increase a business's reach. This creates significant challenges for new businesses to expand their reach and customer base. However, the advancement of mobile, social, and spatial computing has led to the transformation of traditional web-based yellow pages to a mobile format (e.g., location-based social networks; LBSNs). This has allowed businesses that are not in prime locations to become visible to nearby customers. Furthermore, these platforms offer mechanisms that can serve as an affordable advertisement channel to local businesses. Specifically, a business can use LBSNs to promote special offers to customers who connect through the platform. Despite the promising anecdotal evidence, a systematic study of the effectiveness of this LBSN advertising paradigm has not yet been conducted. Using a large time-series data set of approximately 14 million venues in Foursquare, the largest LBSN to date, our work is the first to formally examine the effects of promotions through the platform. Our contribution is twofold. First, we identify no significant and robust evidence that can support the hypothesis of effective promotions for the specific platform. In particular, our main finding is that the probability of observing an increase in daily check-ins or new daily customers to a venue is rarely altered by the presence of a Foursquare promotion. Second, this finding motivates us to design a model that can predict the success of a promotion according to various relevant features. Our model can be used to inform the process of designing and launching successful promotions by evaluating the potential of candidate promotions before their actual release. The practical value of such prelaunch evaluations is elevated by the apparent scarcity of successful promotions, as revealed by our analysis.

KEY WORDS AND PHRASES: and phrases: Bootstrap, difference-in-differences, Foursquare, location-based advertisement, location-based social networks, modeling, social media.

Location has been identified as a critical factor that can decisively affect the success of a business [24, 25, 37]. Specifically, previous relevant work has verified the intuitive causal connection between the location of a business and the volume of potential customers that it has access to. For instance, a business in a crowded urban neighborhood is exposed to more potential customers than a business in a sparsely populated location [26, 38]. Similarly, the reach of a business can benefit from its proximity to a popular landmark or busy hub [36]. The potential of such benefits makes some locations more desirable than others. Predictably, the increased demand raises the setup cost (e.g., rent and taxes) and makes prime locations unattainable for most businesses [18, 42]. Further, even if a business manages to secure a favorable location, it is likely to face fierce competition by businesses that also had the

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means to pay the necessary costs. Previous work has repeatedly verified that, in such competitive settings, it is highly likely to observe "rich-get-richer" phenomena, in which a small subset of the competing businesses claim the lion's share of the customer base [44]. These could be older businesses that had more time to build their reputations and connect with customers, wealthy businesses with superior marketing capabilities, or simply elite competitors that deservedly attract customers with their service quality. On the other hand, businesses outside this "winners' circle" face an uphill battle in their effort to expand their reach and increase their market share, even if they are in a privileged location with access to a large customer base.

Motivated by such challenges, a new location-based advertising outlet has emerged, supported by the advancement and establishment of mobile technology. This outlet is implemented via location-based social networks (LBSNs) with millions of users, such as Foursquare, Yelp, and UrbanSpoon. After partnering with an LBSN, a business gains access to a vast user base. This channel is then used in two ways. First, after users reveal their location to the LBSN, they can use the platform to locate nearby businesses of different types. Thus, a business with a profile on the LBSN can be discovered by potential customers who might otherwise be unaware of its presence. For instance, in the example shown in Figure 1, Alice finds herself in a central business district (CBD, marked with small rectangles),

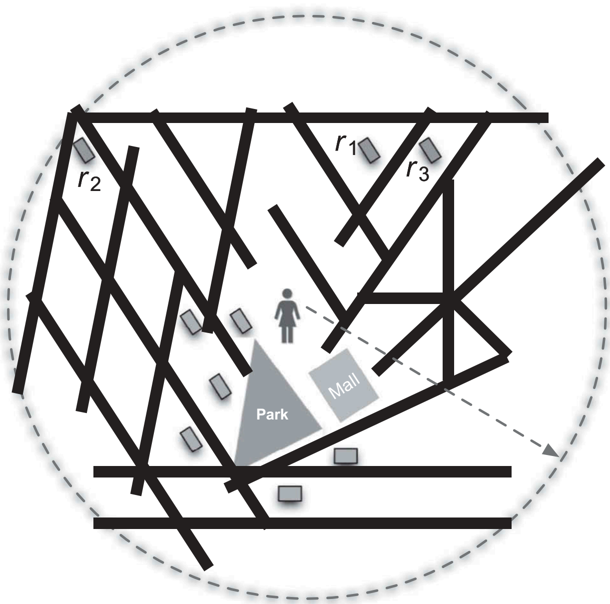


Figure 1. The Location-based Social Media Advertisement Paradigm
Notes. Mobile and Spatial Computing Allows Customers to Discover Establishments in Nonprime Locations (e.g., within the dotted circle). Moreover, It Allows Venues (e.g., r_2 in the figure) to Offer Monetary Incentives through Special Offers to Gravitate Customers Toward Them

which includes a mall, a park, and other amenities. During her visit, Alice is likely to walk by the restaurants within the CBD, given their privileged, central location. However, by using an LBSN, Alice can specify an acceptable range (marked as a dotted circle) and discover less obvious options, such as restaurants r_1, r_2, and r_3. This is a mutually beneficial discovery, which increases both the reach of these restaurants and the number of Alice's options. Nevertheless, Alice could arguably be less willing to seriously consider these less prominent options, as she may be uncertain of their quality. Thankfully, a business can decrease this uncertainty by maintaining an attractive professional profile on the LBSN, including up-to-date information, pictures, and informative reviews [10].

In addition to increasing foot traffic, LBSNs offer business owners additional mechanisms for affordable advertisement. Specifically, a business can use the LBSN's network to promote special offers. Mainstream media are rich with stories on successful promotions through Foursquare [13, 17, 20], the largest LBSN to date. In 2013, a burger joint in Philadelphia reportedly experienced an increase in customers via a campaign on Foursquare, which offered a free beer to users of the popular LBSN to publicly state their presence in the restaurant, an action referred to as a "check-in." Earlier, in 2010, a Milwaukee restaurateur used a promotional campaign to attract 161 Foursquare members into his burger restaurant at the same time. Customers were lured by the promise of the coveted "Swarm badge," which Foursquare awarded if more than 50 users checked-in at a venue at the same time. In the same year, the popular fast-food chain McDonalds launched a Foursquare campaign that offered gift certificates to users who checked-in at certain randomly selected McDonald's locations. Given that the selected locations were not released, users were motivated to visit multiple McDonald's restaurants, leading to a 33 percent increase in the number of check-ins.

Despite the plethora of promising anecdotal evidence, a systematic study of the effectiveness of this advertising paradigm has not been conducted. Our work is the first to address this challenge by studying a large longitudinal data set of about 14 million businesses on Foursquare. Our study formally evaluates both the long- and short-term effects of similar campaigns in Foursquare for participating businesses, while taking into consideration the influence of possible confounding factors. We emphasize here that our results are obtained through a Foursquare data set and, as a result, they might not be transferable to other platforms. However, as alluded to above, Foursquare is the largest LBSN to date, and thus we believe that the conclusions can be fairly indicative of a larger LBSN landscape.

Our main result indicates that the positive effects of special offers through Foursquare are significantly more limited than what anecdotal success stories seem to suggest. In particular, we find no evidence of a statistically significant advantage, in terms of either the number of daily check-ins or those of new customers, for venues that participate in the campaigns in our data set. In addition, to gain a deeper understanding of our results and increase the practical value of our methodology, we design and implement a model for predicting the popularity of a venue during and after a campaign. Our models consider venue-related, promotion-related, and geographical features. Our experiments provide encouraging evidence on the feasibility of this prediction task, which can serve as a practical tool for supporting the design and cost–benefit analysis of similar campaigns. Specifically, we find that a simple logistic regression model is sufficient to achieve 83 percent accuracy with a 0.88 AUC (area under the curve). Further, our findings on the influence of the considered features are fully aligned with our main results, as we find that promotion-related features have only a marginal contribution to the estimation of the promotion's success. Finally, we discuss the implications of our work for businesses as well as for the LBSN platforms. In particular, we describe how our findings can be used to inform strategies for improving campaign effectiveness.

Background and Hypothesis Development

In this section, we first discuss the relevant literature and frame our hypotheses in the context of previous work.

One of the most popular types of promotion includes the offering of a discounted price for a specific product or service. A significant amount of work has been devoted to the study of such discount-based promotions. For instance, Blattberg, Briesch, and Fox [7] found that temporary discounts substantially increase short-term brand sales, even though long-term effects tend to be much weaker. This pattern was further explored by Pauwels, Kanssens, and Siddarth [35], who found that such early beneficial effects on customer purchases tend to fade in subsequent weeks or months. Furthermore, Srinivasan et al. [43] used a vector autoregressive model to quantify the impact of discount promotions on revenue and profit. The authors found that while promotions tend to have a positive impact on manufacturing revenues, the effects for retailers are not straightforward and depend on multiple factors such as brand name and promotion frequency. The issue of promotion frequency was also explored by Kopalle, Mela, and Marsh [28], who proposed a descriptive dynamic model of the effects of discount promotions. Their results suggest that higher-share brands tend to overpromote (i.e., offer promotions too frequently), while lower-share brands do not promote frequently enough.

Promotions on the Web

The establishment of the Web as an effective advertising medium has motivated a long line of literature on promotional efforts that take place in an online setting. In this space, Fulgoni and Morn [21] present data for the positive impact of online display advertising on search lift and sale lift, while Goldfarb and Tucker [22] further examined the effect of different properties of display advertising on its success through traditional user surveys. Papadimitriou et al. [33] study the impact of online display advertising on user search behavior using a controlled experiment, while CARESOME [6] was designed in order to assess the ability of social media to acquire and retain customers.

A recent example of online promotional efforts is the daily-deal business model, adopted by e-commerce firms such as Groupon and LivingSocial. After negotiating with a business and securing discounted prices for a product or service, the daily-deal firm uses the discount as the basis for a promotion that it advertises on its website. A detailed analysis of this model was first presented in Arabshahi [1], while in Dholakia [12] the author surveyed businesses that provide Groupon deals to determine their satisfaction. Edelman, Jaffe, and Kominers [14] considered the benefits and drawbacks of daily-deal promotions for merchants. They presented a model that captures the interplay between advertising and price discrimination effects, as well as the potential benefits to merchants. Byers, Mitzenmacher, and Zervas [9] combined promotion features with information mined from social media to design a predictive model for the popularity of a daily-deal promotion. Their findings challenged the merit of daily-deal promotions, as they reported that venues offering Groupon deals actually saw a reduction in their Yelp ratings after the promotion.

Mobile Marketing and Location-Based Promotions

The pervasiveness of high-speed internet, along with the explosive popularity of smartphones and other mobile devices, have established mobile marketing as a promising strategy for retail businesses to attract, maintain, and enhance the connection with their customers. One of the principal benefits of mobile marketing is knowledge of the user's location at any point. By knowing a user's location, the advertiser can provide customized promotions that are aware of the location's proximity to nearby businesses. Numerous applications and research efforts have been devoted to this new location-based paradigm. Sliwinski [41] built a prototype application that uses customer spatial point pattern analysis to target potential new customers, while Luhur and Widjaja [32] describe a mobile application that can facilitate location-based search for restaurants and promotions. Furthermore, Banerjee and Dohlakia [5] studied the effectiveness of mobile advertising. Their findings indicate that the actual location of the participant as well as the context of that location, significantly influence the potential effectiveness of these advertising strategies. Recently, there have also been efforts to quantify the financial value of location data [4], which are at the center of mobile marketing operations.

Furthermore, the availability of the user's location through time has led to the emergence of location-based social networks, such as Foursquare. LBSN platforms allow users to declare their physical presence at a business (e.g., a restaurant) by "checking-in" online. A business that creates and maintains an informative profile on the LBSN gains access to the LBSN's user base and can use this channel to advertise promotions and attract new customers. Typically, businesses launch promotions to reward users who achieve certain "check-in milestones" with discounts. For instance, a venue can decide to offer a 10 percent discount to the user with the most check-ins in the venue during the past 30 days. LBSNs have become the focus of an increasing number of relevant research efforts. Qu and Zhang [39] proposed a framework for traditional trade area analysis (TA) based on LBSN data. Karamshuk et al. [27] proposed a machine learning framework that uses LBSN data to predict the optimal placement for retail stores. Furthermore, these platforms can serve as mobile "yellow pages" with business reviews that can influence customer choices. For instance, Luca [31] has identified a causal impact of Yelp ratings on restaurant demand using the regression discontinuity framework. Data from LBSNs can also be used to identify peer-influence phenomena with regard to places visited [45], which can further provide insights on "viral" marketing potentials.

Hypothesis Development and Predictive Models for Promotion Success

Despite the growing number of studies devoted to LBSNs, a formal analysis of the success of LBSN promotions has yet to be conducted. This motivates the first part of our work, in which we formulate and study the following two hypotheses using a large-scale data set collected from Foursquare:

> ***Hypothesis 1:*** *Short-term success—the number of customers of a local business increases during a Foursquare promotion.*

> ***Hypothesis 2:*** *Long-term success—the number of customers of a local business increases after a Foursquare promotion.*

The need for two separate hypotheses is motivated by the review of the literature that we presented in this section, which revealed strong evidence that the short-term effects of an advertising campaign are significantly different from its long-term effects [7, 35, 40]. In our hypothesis, the number of customers is a generic *metric* that is realized in our study by two specific quantities. In particular, as we will further elaborate, we evaluate the two hypotheses using: (a) the total number of visits/check-ins (new and repeat customers) to the venue, and (b) the number of unique/new customers who visited the venue during the period examined.

Given the vast number and diversity of Foursquare campaigns, we do not expect to observe identical outcomes for all the promotions in our data set. Instead, we expect that some promotions will be successful while others will not, in either a short- or long-term setting. This motivates the second part of our work, which addresses the following research question:

> *Is it possible to design a predictive model for estimating the short-term and long-term success (both in terms of new and returning customers) of a promotion given its features, the features of the business that runs the promotion, and other contributing factors?*

An accurate predictive model for promotion success can directly inform the efforts of a business to design promotions. In practice, a business can use such a model to evaluate multiple candidate promotions without actually releasing them to the public and identify the most promising option given the circumstances.

Our Data Set

In this section, we briefly describe the data set that we use in our work. Using Foursquare's public venue API (application programming interface) during the seven-month period between October 22, 2012, and May 22, 2013, we queried and obtained information for 14,011,045 venues once every day. Therefore, for every venue we have 213 data points. Each of these readings has the following tuple format: <ID, time, # check-ins, # unique users, # specials, # tips, # likes, tip information, special information>, where:

- ID is the venue identifier
- time is the time of the reading
- # check-ins is the number of total check-ins that have been made in the venue up to the time of the reading
- # unique users is the number of unique Foursquare users that have checked-in the venue up to the time of the reading
- # specials is the number of special promotions that the venue is offering during the time of the reading
- # tips is the number of short reviews left for the venue from Foursquare users up to the time of the reading
- # likes is the number of Foursquare users that have liked the venue up to the time of the reading
- tip information is the text of the short reviews left for the venue up to the time of the reading
- special information includes the details of the promotion offered during the time of the reading (e.g., amount of discount, eligibility requirements, etc.). If no promotion is offered this field is NULL

During the data collection period, a total of 206,163 venues published at least one special. Approximately 45 percent of these venues published only one special. Furthermore, there were a total of 735,034 unique special deals, with 88.68 percent of them provided by venues in the United States. At the time, Foursquare had seven types of specials, namely, "Newbie," "Flash," "Frequency," "Friends," "Mayor," "Loyalty," and "Swarm," each requiring different conditions to be earned [34]. Table 1 presents the description of the different types and their popularity in our data set. As we can observe, "Frequency" is the most popular type of special in our data set, possibly because compared to other types, it appears to be the easiest one to be *unlocked* from many perspectives, covering approximately 86.5 percent of all the offers we collected. For example, a user does not need the *help* of other users as is the case for "Friends" or "Swarm" special deals. Furthermore, the user does not need to compete with other frequent users

Table 1. Type of Specials in Foursquare.

Type	Count	Description
Count/ Newbie	57,710	This type of special is unlocked on a user's first time ever visiting the venue. The objective is to drive new traffic to the venue.
Flash	5,989	Venue sets the number of specials that can be unlocked per day, in a first-come, first-served fashion, or defines an active time window for the special. When the unlock limit is reached, there are no more specials for the day.
Frequency	636,119	Unlocked after every or several check-ins. The objective is to reward users on their routine check-ins.
Friends	5,469	Venue sets the minimum threshold for a group of Foursquare friends. The objective is to reward friends for visiting the establishment together.
Mayor	22,021	This special is awarded to the Foursquare mayor of the venue.
Regular/ Loyalty	6,488	Venue rewards a user every X times they visit, or for coming in X times in total, or for being loyal within a certain period. The objective is to encourage the user to keep coming back to the venue.
Swarm	1,238	A swarm special aims at many people checking-in at the same time. The venue can set a minimum number of Foursquare users (not necessarily friends) who need to check in within a time window in order to unlock the special.

Note: "Frequency" is the most common type provided by Foursquare venues in our seven-month data set.

checking in to this venue as is the case for the "Mayor" special offers. Similarly, he/she is not constrained by time (as in the "Flash" special).

Another parameter of interest for the special offers is their lifespan. Figure 2 presents the empirical CDF (cumulative distribution function) of the offer duration. As we can see, "Frequency" and "Flash" special offers are usually active for a short duration, while "Friends" and "Swarm" usually last for a longer time possibly due to their stricter requirements. The "Mayor" special often lasts even longer, since a customer needs to become the Foursquare *mayor* of the venue to unlock the deal. The *mayorship* is only awarded to the user who has the most check-ins in the venue during the past two months.

As alluded to above, a venue might offer multiple specials during the seven-month data collection period. These multiple specials can be fully overlapped (i.e., they start and end at the same time), partially overlapped, or sequential. We further define a *promotion period* of a venue to be a continuous time period that the venue provides at least one offer and does not include more than two consecutive days without a special offer. In our data set, approximately half of the promotions last for more than a week. While a promotion as defined above can include multiple individual offers, for simplicity we use the terms promotion, offer, campaign, and deal interchangeably in the rest of the study.

Finally, Foursquare associates each venue v with a category/type $T(v)$ (e.g., cafe, school, etc.). This classification is hierarchical, in the sense that an Italian restaurant belongs to the category "Italian restaurant," which can belong to the higher-level category "Restaurants," which can itself belong to the category "Food," and so on. The top level of the hierarchy had nine-categories during the time of data collection; *Nightlife Spots, Food, Shops &*

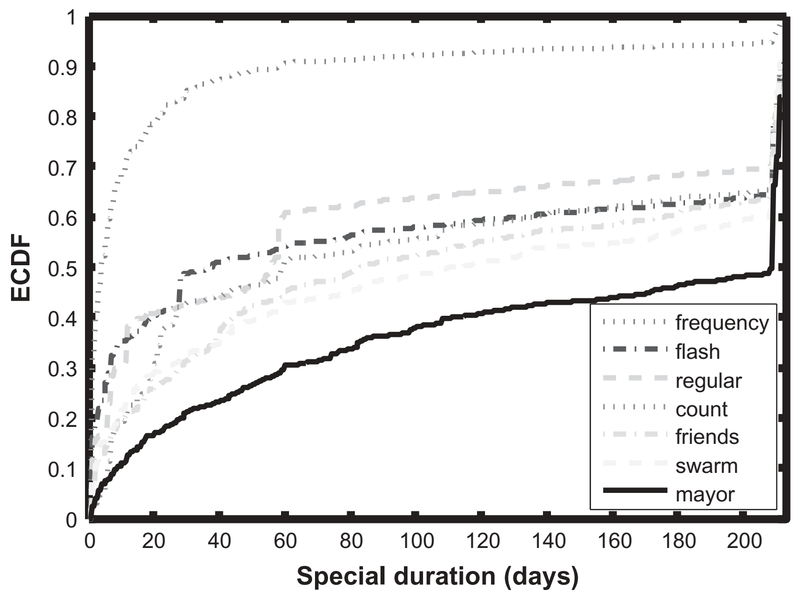


Figure 2. Temporal Distribution for Special Offers
Notes. "Frequency" and "Flash" Specials are Usually Shorter than Other Types of Specials. The "Mayor" Special Often Lasts for a Longer Period of Time

Services, *Arts & Entertainment*, *College & University*, *Outdoors & Recreation*, *Travel & Transport*, *Residences*, and *Professional & Other Places*. From these types, we examine the fraction of venues in each top-level category that offer at least one special deal during the data collection period (Table 2). As we can see "Food," "Nightlife Spots," and "Shops & Services" have the highest chances of offering a special deal (2.54 percent, 3.99 percent, and 1.16 percent, respectively). This can be attributed to the fact that the majority of the venues in these categories are commercial and hence, advertisement is most

Table 2. Food, Nightlife, and Shops & Services Venues Exhibit the Highest Probabilities to Publish a Special Offer in Our Data Set.

Category	# venues	# (%) venues with specials
Nightlife Spots	558,156	6,493 (1.16%)
Food	2,604,408	66,136 (2.54%)
Shops & Services	2,693,300	107,517 (3.99%)
Arts & Entertainment	491,426	5,050 (1.03%)
College & University	493,600	1,923 (0.39%)
Outdoors & Recreation	936,943	1,370 (0.15%)
Travel & Transport	897,404	8,178 (0.91%)
Residences	2,902,492	489 (0.02%)
Professional & Other Places	2,354,975	8,311 (0.35%)

likely among their priorities. While noncommercial venues can also publish specials with the ultimate goal of increasing their visibility, it is certainly less expected and our data verify this.

Defining Promotion Success

As we discussed earlier, we assess the success of LBSN promotions via two alternative measures: (1) the number of check-ins and (2) the number of new customers at the venue. Formally, let $c_v[t]$ and $p_v[t]$ be the time series that encode the daily number of check-ins and the daily number of unique customers at venue v, respectively. These daily time series can be obtained from the data readings described above. In particular, given that each reading for venue v gives us the total number of check-ins in v up to that point, the difference between two consecutive points will give us the number of check-ins that happened during that day. Furthermore, if we take the difference of the number of unique users, this essentially provides us with the number of new users that checked into the venue during the specific day. For venues that run a promotion, we use the first (t_s) and last (t_e) timestamps of the promotion period to split their series into the following periods: (1) before the special campaign, $[t_{s-k}, t_{s-1}]$, (2) during the special campaign, $[t_s, t_e]$, and (3) after the special campaign, $[t_{e+1}, t_n]$. These three segments allow us to analyze the changes that occur for each of the two measures during (short-term) and after (long-term) the promotion. We use 4 weeks of data before and after the promotion. If for a specific venue 28 days of data are not available after the promotion we use as many data points as we have. However, if we have less than a week's worth of data, we do not use this venue for our long-term study.

Creating Reference Groups

Henceforth, we refer to venues from our data set that are attached to a promotion as *treated* venues. We also refer to all others as *untreated* venues. To establish a causal relationship between the promotion campaign and the observed changes in the daily check-ins and/or new customers of a venue, one would ideally be able to design and conduct field experiments in which the covariate distribution between the treated and untreated groups is matched in expectation. Unfortunately, this is not possible in our setting, as we only have access to observational data. In this setting, ignoring the covariate differences between the two groups can introduce a confounding bias. For instance, it might be the case that increasingly popular venues are more likely to run a promotion than others. A naive approach would be to not control for this trend and compare treated and untreated venues from arbitrary popularity levels. However, in that case, an increase in the number of check-ins during or after the promotion might be due to the venue's preexisting trend rather than due to the promotion itself.

To account for such confounding factors, it is imperative to ensure that we only compare treated and untreated venues that are as similar as possible with respect to features with the potential to influence our dependent variables [23]. Specifically, we consider the following features for each venue v: (1) its geographic location loc_v, (2) the type $type_v$, its popularity pop_v prior to the promotion (i.e., the number of total check-ins), and the rate of change $rate_v$ in the venue's daily check-ins prior to the promotion. Given these features, we generate a reference group by strategically sampling a venue v' from the untreated population for each treated venue v. We sample v' so that it has the same location and type as v and minimizes the Euclidian distance from v in the two-dimensional space defined by the numerical popularity and change rate features. Formally, given the untreated population $\mathcal{U}$ and a treated venue v, we select reference venue v' so that $loc_v = loc_{v'}$, $type_v = type_{v'}$ and $v' = argmin_{x \in \mathcal{U}} \sqrt{(pop_v - pop_x)^2 + (rate_v - rate_x)^2}$. Finally, to also account for seasonal and other temporal effects, we extract the timeframe of the sampled venue v' that corresponds to the promotion (and the windows of interest before and after the promotion) of the treated venue v. The reference group thus includes a matching venue for each venue in the treated group. We repeat the process 20 times to generate 20 reference groups for our experiments.

The members of each reference group are removed from the untreated population $\mathcal{U}$ after the group has been completed, to ensure diversity and no overlap among the 20 groups. We use these 20 nonoverlapping reference groups in the two experiments that we describe in the following section.

Evaluating the Success of Foursquare Promotions

Our objective is to identify and analyze the promotions in our data set that are associated with a statistically significant change in the number of check-ins and/or the number of new customers. Formally, let $m^b_{c_v}$, $m^d_{c_v}$, and $m^a_{c_v}$ be the mean number of check-ins for venue v before, during, and after the promotion, respectively. The following two-sided hypothesis test examines whether there is a statistically significant change in the short-term with respect to the number of daily check-ins:

$$H_0 : \; m^b_{c_v} = m^d_{c_v} \tag{1}$$

$$H_1 : \; m^b_{c_v} \neq m^d_{c_v}. \tag{2}$$

The sign of the observed difference will further inform us if the change is positive. A similar hypothesis test is used to examine the long-term effectiveness of a promotion as well as the impact of the promotion on the unique customers for the venue. In all cases a significance level of $\alpha = 0.05$ is used.

Rather than use a standard t -test that implicitly makes ambiguous assumptions about the distribution of the dependent variable, we opt for a more robust approach based on bootstrap hypothesis testing [15]. This method also allows us to estimate the statistical power π of the performed test. This is important since an underpowered test might be unable to detect statistically significant changes especially if the effect size and/or sample size are small. Consequently, this can lead to underestimation of the cases where the alternative hypothesis is true.

Statistical bootstrap [15] is a robust method for estimating the unknown distribution of a population's statistic when only a sample of the population is known. In the absence of any other information about the population, we assume that the observed sample contains all the available information for the underlying distribution. Thus, the most robust method of estimating this distribution is to draw a large number of subsamples with replacement from the available sample. In addition to delivering very accurate estimates of the target distribution, bootstrap can be adopted to retain any dependencies between consecutive data points in time-series data such as ours [29] as we describe in the following. Next, we describe the bootstrap process in a short-term setting with the mean number of check-ins as the dependent variable. The respective processes for the long-term setting and our second dependent variable (i.e., the mean number of new users) trivially follows.

Our input for each venue consists of two contiguous segments of the venue's time series that encodes the number of check-ins. The first segment corresponds to the window before the promotion, and the second one to the window during the promotion. First, we re-center both segments around zero by subtracting their respective means from their values. This ensures that the null hypothesis is true (i.e., the two samples have the same mean). We then draw 5,000 random paired samples with replacement from the two segments and compute the difference between each pair. This allows us to build the distribution of the difference $m_{c_v}^d - m_{c_v}^b$, under H_0. Note that here we do not sample single points but pairs. This is the block bootstrap approach, which ensures that any dependencies between consecutive points will be retained and is used with time-series data [29].

If the $1 - \alpha$ confidence interval of $m_{c_v}^d - m_{c_v}^b$ under the null hypothesis does not include the observed value from the data, then we can reject H_0. We also obtain an empirical p-value by computing the fraction of bootstrap samples that led to an absolute difference equal to or greater than the one observed in the data, that is, $\left|m_{c_v}^d - m_{c_v}^b\right|$. In addition, we estimate the power π of the statistical test by following exactly the same process as above, but without centering the samples to a zero common mean. This allows us to build the distribution of $m_{c_v}^d - m_{c_v}^b$ under H_1. The power of the test is then computed as the overlap between the critical region and the area below the distribution curve under H_1.

Finally, after applying the above test to each one of the promotion venues we calculate the fraction of promotions associated with a statistically significant increase in the average number of daily check-ins. The fraction includes promotions with a p-value less than $\alpha = 0.05$ or $\pi \geq 0.8$. The latter is a standard threshold for statistical power and increases our confidence that failure to reject H_0 is not due to an underpowered test. With this we essentially calculate the probability of an increase in the mean check-ins during the promotion period, $P(I_{c,d}|E,S)$, where $I_{c,d}$ is the event of a check-in increase during the promotion, S is the presence of a special offer, and E captures various environmental externalities that can affect $I_{c,d}$ and are potentially unobserved. We also perform exactly the same analysis for the reference venues. The corresponding fraction provides us with the probability $P(I_{c,d}|E)$, since the matching process allows us to assume that the treated and reference venues are exposed to the same externalities. We report the short- and long-term results for the number of check-ins in Figure 3. We then report the respective results for the number of new customers in Figure 4. As we can see, $P(I_{+,*}|E) \approx P(I_{+,*}|E,S)$. This suggests that the presence of a local promotion and the increase in the average check-ins are conditionally independent given the externalities E! To be more precise, during the promotion period the probability of increase in the check-ins for the treated venues appears to be larger than that of the reference venues. However, when considering the confidence intervals of $P(I_{+,*}|E)$ presented in Figures 3 and 4, we can see that this increase is very small from a practical perspective.

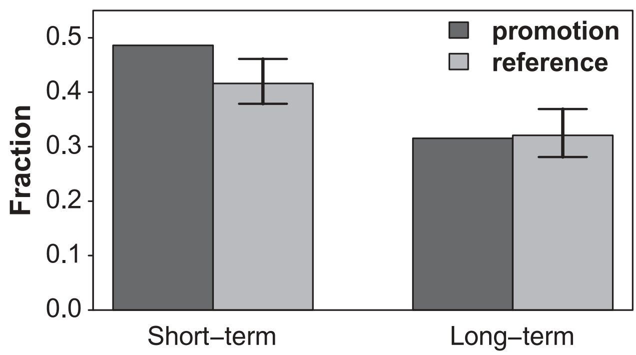


Figure 3. Results of the Bootstrap Hypothesis Testing for the Number of Check-ins

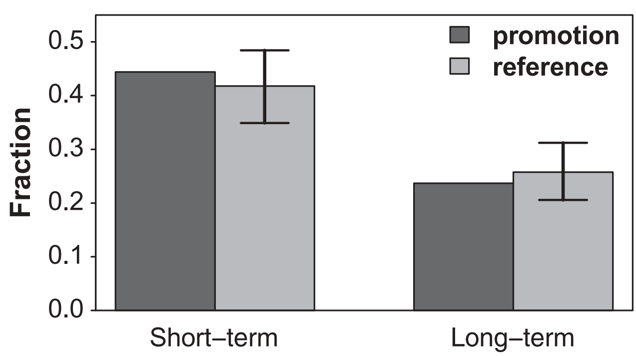


Figure 4. Results of the Bootstrap Hypothesis Testing for the Number of New Customers

In conclusion, our analysis reveals that, despite the popularity of Foursquare promotions among merchants, the benefits for the promoted venues tend to be limited and applicable only in a short-term setting.[1]

Predicting Promotion Success

In this section, we present two separate predictive models for short- and long-term promotion success. In both settings, we treat the prediction problem as one of binary (success/failure) classification. We populate the dependent variables according to the bootstrap test that we described in the previous section. Specifically, the positive class includes the promotions that are associated with a statistically significant increase in $m^d_{c_v}$ $\left(m^a_{c_v}\right)$, while the negative class includes the promotions with a statistically significant decrease or a failure to reject the null hypothesis with a powerful test $\pi \geq 0.8$. To keep our presentation focused and concise we present only our results for the number of check-ins and omit our results for the number of new customers since they are very similar.

Next, we describe the different types of features that we used to populate the set of independent variables for our prediction task.

Feature Extraction

Venue-related features ($\mathcal{F}_v$)

The set $\mathcal{F}_v$ includes features related to the properties of the venue that is running the promotion. The intuition behind extracting such features is that the effectiveness of the special offer can be connected to the characteristics of the venue itself. For instance, a promotion that is not helpful for an unpopular venue might offer a great boost to a moderately or highly popular venue. The features in $\mathcal{F}_v$ include:

Venue type: This is the top-level type $T(v)$ of venue v. Table 3 depicts the fraction of special deals offered from different types of venues that are associated with a statistically significant increase in the daily number of check-ins, that is, the conditional probability $P(I|T(v))$.

Table 3. Probability for the Positive Class Conditioned on the Type of Venue (%).

Category		Nightlife	Food	Shops	Arts	College	Outdoors	Travel	Residence	Professional
% Positive class	Short-term	62.07	57.74	42.90	52.87	56.25	58.33	66.84	54.54	61.86
	Long-term	50.00	41.51	28.22	43.75	37.04	25.00	53.80	14.29	39.68

Popularity: For venue popularity we use two separate features: (1) the mean number of check-ins per day at the venue for the period before the special offer starts, $m^b_{c_v}$, and (2) the cumulative number of check-ins in v just before the beginning of the special offer, $c_{a_v}[t_{s-1}]$.

Loyalty: We define the loyalty λ of users in venue v as:

$$\lambda_v[t_{s-1}] = \frac{c_{a_v}[t_{s-1}]}{p_{a_v}[t_{s-1}]}, \tag{3}$$

where $p_{a_v}[t_{s-1}]$ is the accumulated number of unique users that have checked in to venue v at time t_{s-1}. A high-level λ indicates the average return (check-in) rate of users in v.

Rating Score: Each venue in Foursquare has a rating score ranging from 0 to 10. Foursquare calculates this rating based on a number of signals [19] such as the number of positive/negative reviews that the venue has received from Foursquare users. We use the rating $\gamma_v[t_{s-1}]$ of venue v at time t_{s-1} as another feature.

Likes: Foursquare allows users to like or dislike a venue. We use the accumulated number of likes $l_v[t_{s-1}]$ a venue has received (at time t_{s-1}) as a feature for our classifiers.

Tips: Foursquare allows users to leave short reviews for the venues. We use the total number of such reviews (tips in Foursquare's terminology) $N_{t_v}[t_{s-1}]$ for venue v up to time t_{s-1} as a feature for our classifiers.

Promotion-Related Features ($\mathcal{F}_p$)

The set $\mathcal{F}_p$ includes features related to the details of actual promotion that the venue is running. For instance, a short-lived offer might have no impact because people did not have a chance to learn about it. The features in $\mathcal{F}_p$ include:

Duration: The duration D is the promotion period length. Intuitively, a longer duration allows users to learn and "spread the word" about the promotion, which consequently will attract more customers to check in to the venue.

Type: Seven promotion types can be offered from a Foursquare venue during the promotion period. Each type provides different kind of benefits but also has different unlocking constrains. Table 4 shows the probability distribution of the positive class conditioned on the different types of special offers that are part of the promotion.

If a venue publishes two (or more) different types of deals we refer to this as a "Multitype" offer. To be able to easily distinguish between different combinations of offers in these "Multitype" deals, we encode this categorical feature in a binary vector $\xi_s \in \{0, 1\}^7$, where each element represents a special type. "Multitype" promotions will have multiple non-zero elements.

Count: Count N_s is the average number of special deals per day associated with a promotion period. N_s captures how frequently a venue

Table 4. Probability Distribution of the Positive Class Conditioned on the Different Types of Special Offers (%).

Type		Newbie	Flash	Frequency	Friends	Mayor	Loyalty	Swarm	Multitype
% Positive class	Short-term	62.24	60.00	45.56	84.62	67.74	50.50	57.14	60.60
	Long-term	59.32	62.50	30.07	43.75	54.84	50.00	0.00	44.23

published specials during a specific promotion period. Note that ξ_s is a binary vector and hence, if a venue is offering two deals of the same type this can only be captured through N_s.

Geographical Features ($\mathcal{F}_g$)

The effectiveness of a promotion can also be related to the urban business environment in the proximity of the venue. The latter can be captured through the spatial distribution of venues. For example, an isolated restaurant might not benefit from a special deal promotion, simply because people do not explore the specific area for other attractions. For our analysis, we consider the neighborhood $\mathcal{N}(v, r)$ of a venue v to be the set of venues within distance r miles from v (we use $r = 0.5$).[2] The features in $\mathcal{F}_g$ include:

Density: We denote the number of neighboring venues around v as the density ρ_v of $\mathcal{N}(v, r)$. Hence,

$$\rho_v = |\mathcal{N}(v, r)|. \tag{4}$$

Area Popularity: The density ρ_v captures a static aspect of v's neighborhood. To capture the dynamic aspect of the overall popularity of the area, we extract the total number of check-ins observed in the neighborhood at time t_{s-1}:

$$\phi_v = \sum\nolimits_{v' \in \mathcal{N}(v,r)} c_{a_{v'}}[t_{s-1}] \tag{5}$$

Intuitively, a more popular area could imply higher likelihood for Foursquare users and potential customers to be in the area, learn about the promotion, and be influenced to visit the venue.

Competitiveness: A venue v of type $T(v)$, will compete for customers only with neighboring venues of the same type. Hence, we calculate the proportion of neighboring venues that belong to the same type $T(v)$:

$$\kappa_v = \frac{|v' \in \mathcal{N}(v, r) \wedge T(v') = T(v)|}{\rho_v}. \tag{6}$$

Neighborhood Entropy: Apart from the business density of the area around v, the diversity of the local venues might also be important. To capture diversity we typically rely on the concept of information entropy. In our setting we calculate the entropy of the distribution of the venue types in $\mathcal{N}(v, r)$. With f_T being the fraction of venues in $\mathcal{N}(v, r)$ of type T, the entropy of the neighborhood around v is:

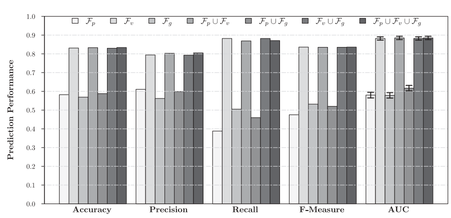
$$\varepsilon_v = -\sum\nolimits_{T \in \mathcal{T}} f_T \cdot log(f_T) \tag{7}$$

where, $\mathcal{T}$ is the set of all (top-level) venue types.

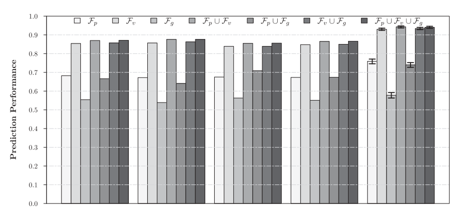
Predictive Models

In this section, we turn our attention to supervised learning models and we combine the extracted features to improve the performance achieved by each of them individually. We evaluate various combinations of the three types of features for the two different problems we consider: (a) classification and (b) (continuous) regression. Our performance metrics include accuracy, precision, recall, *F*-measure, and AUC. We examine two different models, a linear one (i.e., logistic regression) and a more complex one based on ensemble learning (i.e., random forest).

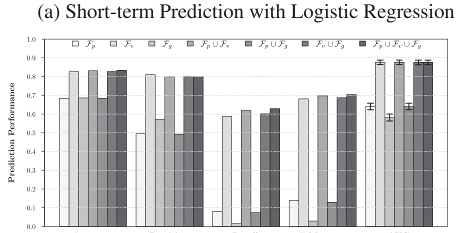
We begin by evaluating our models through 10-fold cross-validation on our labeled promotion data set. The results for the different combinations of features and for the different classifiers are shown in Figure 5. As the results indicate, even simple linear models perform very well, achieving high values of precision, recall, accuracy, and AUC. It is also interesting to note that the most important type of features appears to be the venue-related ones $\mathcal{F}_v$. The promotion-related $\mathcal{F}_p$ as well as the geographic features $\mathcal{F}_g$ while improving the classification performance when added, do not provide very



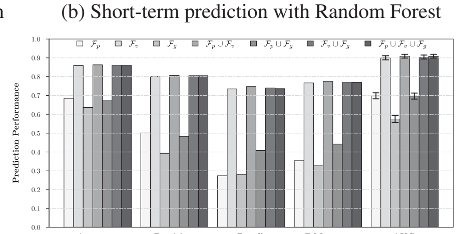
(a) Short-term Prediction with Logistic Regression



(b) Short-term prediction with Random Forest



(a) Short-term Prediction with Logistic Regression



(d) Long-term prediction with Random Forest

Figure 5. Prediction Performance Using 10-Fold Cross-Validation

large improvements. Tables 5–8 further present the confusion matrices for the two models for both the long- and short-term prediction problem.

The above models were built and evaluated on the data points identified through the bootstrap statistical tests in an effort to keep the false positives/negatives of the labels low. However, while this is important for building a robust model, in a real-world application the model will need to output predictions for cases that might not provide statistically significant results a posteriori. After all, a venue owner is interested in what he observes, and not whether this was a false positive/negative (i.e., an increase/decrease that happened by chance). Hence, we test the performance of our models on the data points in the promotion group for which we were not able to identify a statistically significant change ($\alpha = 0.05$) in the average number of check-ins per day. A positive observed value of the difference corresponds to the positive class. Note that we do not use these points for training. This resembles an out-of-sample evaluation of our models, testing their generalizability to less robust observations. Our results are presented in Figure 6. While, as one might have expected, the performance is degraded compared to the cross-validation setting, it is still good.

Table 5. Confusion Matrix for Short-term Prediction with Logistic Regression

		True Class	
		Negative	**Positive**
Predicted Class	Negative	2,394	366
	Positive	598	2,462

Table 6. Confusion Matrix for Long-term Prediction with Logistic Regression

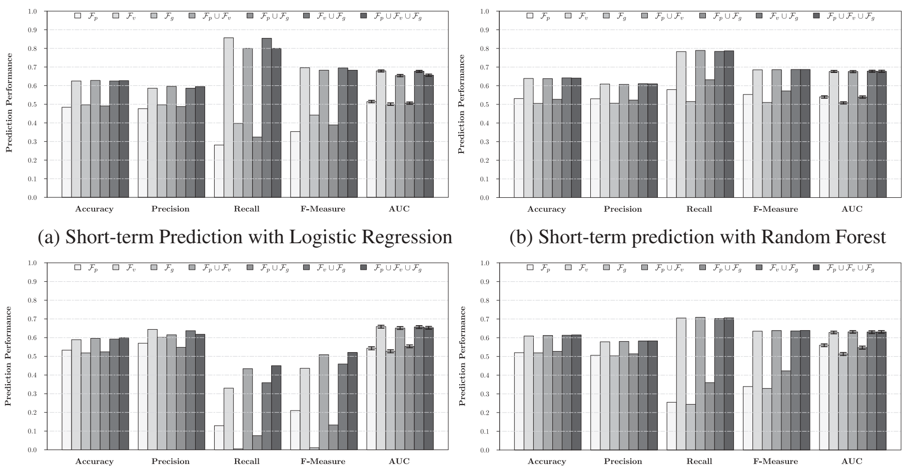
		True Class	
		Negative	**Positive**
Predicted Class	Negative	2,718	501
	Positive	213	849

Table 7. Confusion Matrix for Short-term Prediction with Random Forest

		True Class	
		Negative	**Positive**
Predicted Class	Negative	2,650	407
	Positive	342	2,421

Table 8. Confusion Matrix for Long-Term Prediction with Random Forest

		True Class	
		Negative	**Positive**
Predicted Class	Negative	2,690	356
	Positive	241	994



(a) Short-term Prediction with Logistic Regression (b) Short-term prediction with Random Forest

(c) Long-term prediction with Logistic Regression (d) Long-term prediction with Random Forest

Figure 6. Out-of-Sample Prediction Performance

Next, we examine the logistic regression coefficients of the various features used. The results are presented in Table 9, where we have standardized the variables for better comparisons. Considering both the statistical significance of the coefficients and their magnitude we can see that the most important feature appears to be the popularity of a venue as captured by the number of check-ins prior to the promotion. In particular, considering the direction of the effects for the two independent variables that capture the popularity of a venue, we can see that popular venues with a large number of cumulative check-ins, which, however, exhibit smaller mean daily check-ins during the period prior to the promotion, appear to be more likely to benefit from a promotion. Very popular venues, such as those with a large number of cumulative techniques, are expected to temporarily lose clientele, because there is a saturation at the population level. However, promotions appear to help these venues increase their daily check-ins again. From the rest of the features, the area popularity ϕ_v and neighborhood entropy ε_v appear to be important for both the short- and long-term success of a promotion. Large diversity of (popular) venues in an urban area creates more opportunities for people to visit the area, and hence for venue v to benefit from running a promotion on Foursquare. Furthermore, focusing on

Table 9. Coefficients for Logistic Regression with Standardized Numerical Features.

		Est. Signif.			Est. Signif.
	(Intercept)	-0.642		(Intercept)	-1.238*
$\mathcal{F}_v$	$c_{a_v}[t_{s-1}]$	5.232***	$\mathcal{F}_v$	$c_{a_v}[t_{s-1}]$	5.559***
	$m^b_{c_v}$	-10.792***		$m^b_{c_v}$	-10.487***
	$\lambda_v[t_{s-1}]$	-0.066.		$\lambda_v[t_{s-1}]$	-0.075
	$\gamma_v[t_{s-1}]$	-0.495***		$\gamma_v[t_{s-1}]$	-0.252***
	$l_v[t_{s-1}]$	-0.058		$l_v[t_{s-1}]$	0.665***
	$N_{t_v}[t_{s-1}]$	0.162.		$N_{t_v}[t_{s-1}]$	-0.159
$\mathcal{F}_p$	D	0.256***	$\mathcal{F}_p$	D	-0.296***
	N_s	0.174**		N_s	0.055
$\mathcal{F}_g$	ρ_v	-0.696*	$\mathcal{F}_g$	ρ_v	-0.806**
	ϕ_v	0.817**		ϕ_v	1.122***
	κ_v	-0.062		κ_v	-0.038
	ε_v	0.102**		ε_v	0.079.
not verified		*Reference level*	not verified		*Reference level*
	verified	-0.026	verified	-0.589	
Category	Arts	*Reference level*	Category	Arts	*Reference level*
	College	-0.777		College	-1.161
	Food	0.069		Food	0.922*
	Nightlife	0.227		Nightlife	1.369.
	Outdoors	0.700		Outdoors	1.122
	Residence	-1.845*		Residence	-2.138
	Shops	-0.529		Shops	0.633
	Travel	0.735.		Travel	1.769***
	Work	-0.511		Work	0.801
Type	Newbie	*Reference level*	Type	Newbie	*Reference level*
	Flash	0.726		Flash	1.909*
	Frequency	-0.501**		Frequency	-0.976**
	Friends	1.261*		Friends	-1.117
	Mayor	0.979**		Mayor	0.260
	Regular	0.221		Regular	-0.466
	Swarm	0.269		Swarm	-13.153
	Multitype	-0.640**		Multitype	-0.982
	(a) Short-term			(b) Long-term	

Signif. levels: 0 *** 0.001 ** 0.01 * 0.05 . 0.1

the venue type we see that, in general, no specific type of venue is associated with positive (or negative) results for the promotion. The interesting observation is the negative (and significant) impact of a promotion for venues of the type *Residence*. These are rental apartment buildings and it is possible that a promotion on Foursquare serves as a negative signal for rental prospects. On the contrary, the venues of the type *Travel* are the ones that appear to benefit the most and significantly from a statistical point of view. The reason for this is that these types of places typically attract tourists, and

Foursquare promotions might be an effective way to influence people who are not familiar with an area to decide on a place to go.

Our random forest classifier is very large to effectively visualize. However, we can evaluate the importance of every feature in the classification by using the Gini importance coefficient [8]. Figure 7 presents our results, where the higher the value of the coefficient for a feature the more important the feature is for the classification. As we can see, the popularity of a venue is the most important feature for the random forest classifier as well. The rest of the features, while exhibiting some nonzero importance, are much less crucial; a result consistent with our discussion for the logistic regression model.

Finally we focus on the results of logistic regression, which has a genuine probabilistic interpretation. In particular, accuracy performance when using the set of features $\mathcal{F}_v \cup \mathcal{F}_g$ and $\mathcal{F}_p \cup \mathcal{F}_v \cup \mathcal{F}_g$ is very similar. We compute the actual outcome of the model, that is, before applying the classification threshold, which is the probability of observing an increase in the mean daily check-ins of the corresponding venue. Hence, the outcome of the two models provides the probabilities $P(I|\mathcal{F}_v, \mathcal{F}_g)$ and $P(I|\mathcal{F}_p, \mathcal{F}_v, \mathcal{F}_g)$, respectively. Table 10 presents the root mean square differences between these probabilities for the various cases examined, which is small for all scenarios. Since features $\mathcal{F}_v$ and $\mathcal{F}_g$ capture various (environmental) externalities, while the set $\mathcal{F}_p$ captures attributes related to the promotion itself, these results further support the findings from our

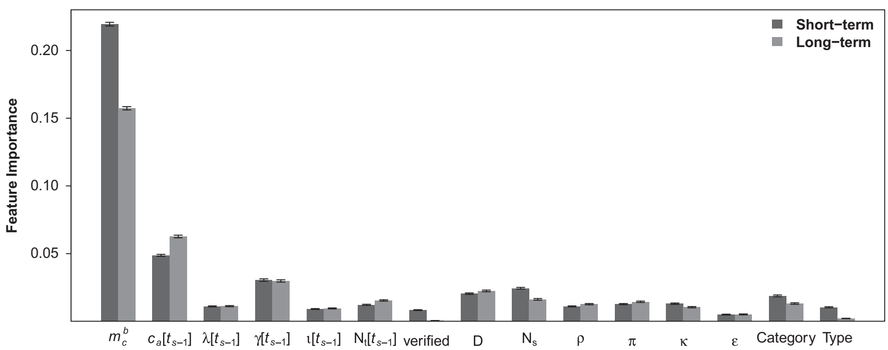


Figure 7. Gini Importance for the Random Forest Features

Table 10. The Root Mean Square Distance of the Logistic Regression Output for the Features $\mathcal{F}_v \cup \mathcal{F}_g$ and $\mathcal{F}_p \cup \mathcal{F}_v \cup \mathcal{F}_g$ Further Supports Our Statistical Analysis.

Cross-validation		Out-of-sample	
Short-term	**Long-term**	**Short-term**	**Long-term**
0.081	0.067	0.072	0.074

earlier statistical analysis. Of course, these features do not capture all the externalities, and thus the actual probabilities might differ, even though the classification outcome is very accurate.

Discussion and Limitations

Our results suggest that the benefits from local promotions through Foursquare are much more limited than what anecdotal accounts suggest. However, we acknowledge that the time series of daily check-ins and unique users serve only as a proxy for the actual revenue generated. Nevertheless, we believe that these proxies can indirectly drive revenue, by increasing the *visibility* of a venue. In addition, customers attracted by these campaigns are arguably more motivated to check in than others. In fact, as we discussed earlier Foursquare campaigns *require* users to check in to claim their badges, discounts, or other types of rewards. Therefore, a revenue increase due to the influx of such customers should be reflected in these proxies. Of course, one can use other metrics as proxies for the evaluation such as the percentile increase of check-ins in a venue or the *market share* of a venue in the neighborhood. The latter captures interactions with neighboring competing venues, as it represents the fraction of check-ins in venues of the same type that were generated in the venue offering the promotion.

Even though our study suggests the limited potential of such campaigns on Foursquare, we choose to use these findings as motivation for improving the design of similar advertising efforts. In this direction, the promising results of our predictive models suggest the usefulness of such methods for the purpose of estimating the effectiveness of alternative campaign designs and choosing the best possible option for each setting.

Further, recent relevant work has exposed reasons why people check in to venues [30], while design flaws that can explain some of the shortcomings of current LBSN campaigns have also been identified. For example, Cramer, Rost, and Holmquist [11] revealed possible reasons that lead people to check in to a location long after they arrive. It is likely that these users might not have used the LBSN to discover nearby venues during their visit and would thus be oblivious to any location-based campaigns. This suggests the need for more active communication channels, such as geo-fenced push notifications. In fact, Fang et al. [16] showed through randomized experiments that *active notifications* for location-aware mobile promotions could generate 12 times more sales as compared to conventional notifications. Moreover, the way that a promotion is redeemed might also play a role. For example, a large fraction of the promotions on Foursquare limit their scope to users that have a particular credit card (e.g., American Express). While such constraints are typically motivated by agreements with credit card companies or with other third-party vendors, further research is required to verify whether the benefits outweigh the cost of eliminating a significant part of the customer base.

Conclusions

In this work, we study the effectiveness of special deals that local establishments can offer through LBSNs using data collected from Foursquare. In particular, we collect and analyze a large data set from Foursquare using randomization and statistical bootstrap. We find that promotions through this platform do not alter the probability of observing an increase in the daily check-ins or the daily new customers to a venue. We also model the effectiveness of such offers by extracting three different types of features and building classifiers that can provide us with an educated decision with regard to the success of these promotions. Finally, our analysis sheds light on ways to implement a promotion mechanism that can be more effective and useful for local businesses.

Acknowledgments

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NOTES

1. To further validate our findings we employ an alternative testing method that we present in the Appendix for interested readers.
2. We also used $r = 0.3$ and $r = 0.8$ and obtained similar results.

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Appendix

Difference-in-Differences

We analyze our data using an alternative method from the econometrics literature, namely, difference-in-differences (DD) [2]. This is a quasi-experimental technique, visualized in Figure A1, Because they are included in the Appendix, Figures 8, 9, and 10 have been renumbered A1, A2, and A3, respectively. Please check that that the figures are still called out correctly in the Appendix which aims to identify the effect of a treatment using observational data. We conduct this secondary analysis to strengthen our confidence in the surprising findings that we reported with our bootstrap hypothesis testing.

DD requires observations obtained in different points in time, for example, t_1 and t_2 ($t_1 < t_2$), for both the control (e.g., $y_{c,1}$ and $y_{c,2}$) and the treated

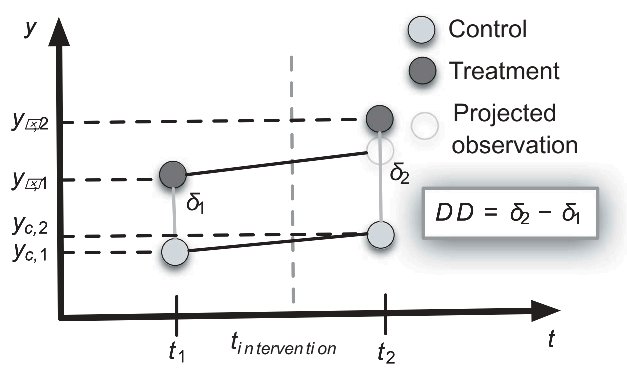
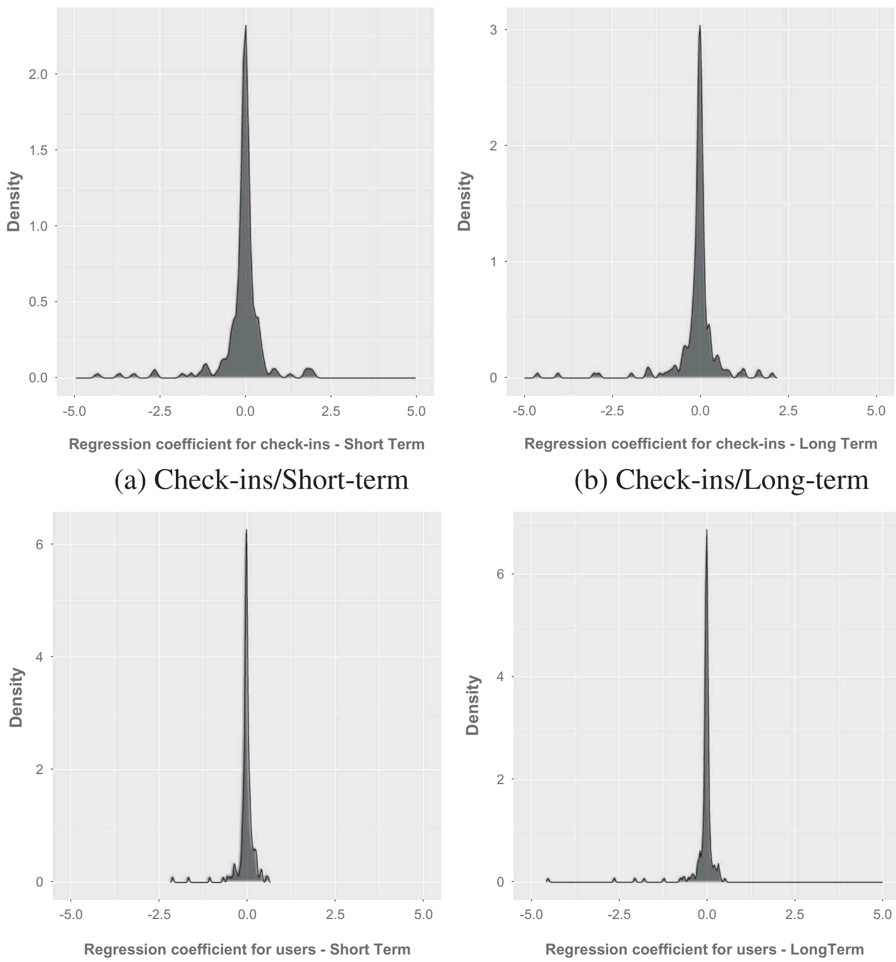


Figure A1. The Difference-in-Differences Method

(e.g., $y_{\tau,1}$ and $y_{\tau,2}$) subjects. The treated subject is exposed to the treatment only during t_2. The difference between $y_{\tau,2}$ and $y_{c,2}$ then includes the effect of the treatment, as well as other "intrinsic" differences between the treatment and the control. The latter can be captured by their difference during time t_1, that is, $y_{\tau,1} - y_{c,1}$, in which no treatment has been applied. The DD estimate is then:

$$\delta_{\tau,c} = \left(y_{\tau,2} - y_{c,2}\right) - \left(y_{\tau,1} - y_{c,1}\right). \tag{A1}$$



(a) Check-ins/Short-term (b) Check-ins/Long-term

(c) Unique Users/Short-term (d) Unique Users/Long-term

Figure A2. Difference-in-differences Results

Notes. The Average Difference-in-Differences in All Scenarios is Statistically not Different from 0! This Strengthens our Conclusions from our Bootstrap Tests, that the Impact of Promotions through Location-Based Social Media is not as Strong as Anecdotal Accounts Suggest

This process removes any biases that could be the result from (12) permanent differences between treatment and control subjects, as well as (2) temporal biases that could be the result of trends instead of the actual treatment. The DD estimate can be formally obtained through a linear regression that models the dependent variable y.

In our setting, the treatment is represented by the presence of a promotion. We conduct separate analyses for our two measures of promotion success (i.e., the average number of check-ins and the average number of new customers), which we use to populate the dependent variable y. For our study on the short-term effects of the LBSN promotion, time t_1 considered by the DD method corresponds to the period prior to the special offer, while t_2 corresponds to the period during the promotion. For the long-term study, t_1 again corresponds to the period prior to the special offer, while t_2 corresponds to that after the promotion is over.

To reiterate, each treated venue is matched with exactly one untreated venue from each of our 20 reference groups. Thus, for each treated venue in our data set, we first compute its mean DD estimate over all 20 matches. Figure A2 depicts the distribution of the mean DD for the promotion venues for both of our dependent variables (i.e., check-ins and new users) in both a short- and long-term setting. The figure reveals that, in all four cases, the values are heavily concentrated around $\delta = 0$. In addition, the corresponding p-values for the corresponding statistical test $H_0: \bar{\delta}_{\tau,c} = 0,\ H_1: \bar{\delta}_{\tau,c} > 0$ are greater than 0.05 for all four cases. Therefore, we do not find enough evidence to reject the null hypothesis, which corresponds to the fact that the promotion has no effect on the dependent variables (i.e., the average DD is practically 0). Before concluding our DD analysis it is important to note here that a crucial assumption for the method's robustness is that of the parallel trend, which we examine below.

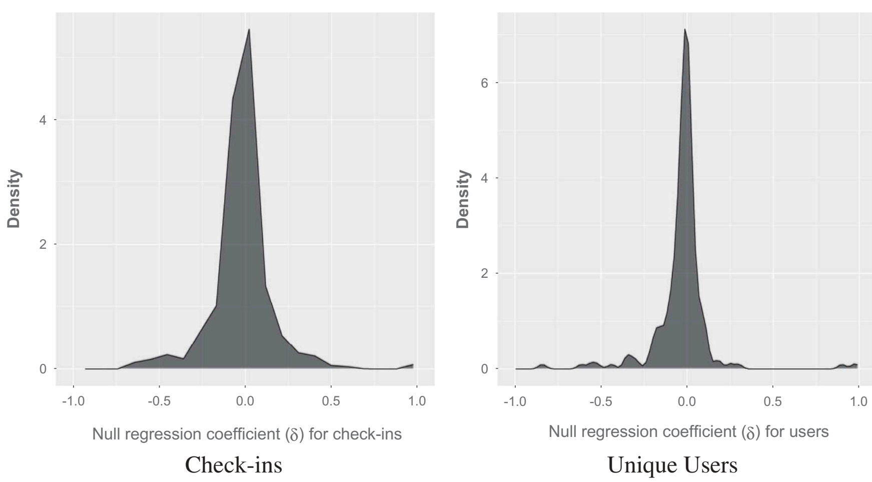


Figure A3. Parallel Trend Assumption
Notes. The Parallel Trend Assumption is Satisfied in our Data Set for both Daily Check-ins and Daily New Users

In conclusion, these results verify our initial findings on the limited impact of promotional campaigns on both the number of check-ins and the number of new visitors of a venue. It is important to stress that the results of our two methods do not imply the failure of all promotional campaigns included in our data set or the futility of LBSN promotions in general. For instance, the DD results in Figure A2 verify the success of some cases, even though the vast majority of the points were concentrated around zero.

Finally, we consider this negative result as motivation for merchants and researchers to revisit their use of LBSN promotions and work toward a methodology that significantly improves the outcomes of the promoted business. We describe a step in this direction in the following section, in which we present a predictive model that can accurately estimate the success of a promotion based on different types of features. As we discuss in detail, a business can use our model to evaluate multiple candidate promotions without actually launching them and identify those with the highest probability of success.

Testing the Parallel Trends Assumption of the Difference-in-Differences Method

For the difference-in-differences method to provide robust results, the parallel trend assumption between treated and control subjects needs to be satisfied. We visualize this assumption in Figure A1, where we see that the parallel trend between the treatment and the control subjects allows the DD method to report the true difference $\delta_2 - \delta_1$ as the DD estimate. To test whether this assumption is satisfied in our data set, we can compute the difference-in-differences between the treated and the control venues for earlier time periods that do not include the presence of a promotion. If the computed difference-in-differences is insignificant, that is, $\delta = 0$ for all statistical purposes, then the parallel trend assumption holds [3]. In our case we use the one-month period prior to the special promotion. We consider a "pseudo-intervention" at the middle of this period, that is, two weeks, and we compute the difference-in-differences coefficient between the two null time periods. The results are presented in Figure A3. As we can see, the estimated null DD coefficient is distributed around 0. In fact, the corresponding *t*-tests for the daily check-ins and unique users fail to reject the null hypothesis (p-value > 0.15), that is, they are equal to 0. Thus, we can conclude that the parallel trend assumption holds.

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