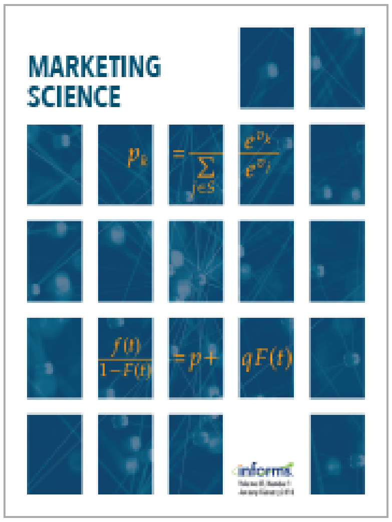

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Inspiration from the "Biggest Loser": Social Interactions in a Weight Loss Program

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Abstract. We investigate the role of heterogeneous peer effects in encouraging healthy lifestyles. Our analysis revolves around one of the largest and most extensive databases about weight loss that track individual participants' meeting attendance and progress in a large national weight loss program. The main finding is that, although weight loss among average-performing peers has a negative effect on an individual's weight loss, the corresponding effect for the top performer among peers is positive. Furthermore, we show that our results are robust to potential issues related to selection into meetings, endogenous peer outcomes, individual unobserved heterogeneity, lagged dependent variables, and contextual effects. Ultimately, these results provide guidance about how the weight loss program should identify role models.

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Keywords: big data • customer relationship management • healthy living • subscription services • weight management

1. Introduction

Healthy lifestyles are valued by customers and firms alike. In addition to direct behavioral interventions (e.g., Hagen et al. 2016), such lifestyles may in fact propagate throughout a social network via interactions and peer effects as indicated by past research showing peer effects in health outcomes (e.g., Christakis and Fowler 2008). However, not all peers are alike, and thus, each peer's impact on others within the group need not be homogeneous. In light of this heterogeneity, how should firms identify role models in their efforts to promote healthy lifestyles?

Our research studies the impact of heterogeneous peer effects under the context of a large weight loss program in the United States, where social support from peers may play an important role in weight loss. The weight loss industry in the United States is particularly large and generates about $20 billion each year from over 100 million dieters. From a commercial weight loss program's perspective, customer-centric program design policies aimed to shape and optimize the interactions between participants may have a positive impact on the level of engagement. Most importantly, customer satisfaction and development will likely be tied to the perceived performance of the program (e.g., Anderson et al. 1994 and Kumar et al. 2014) as reflected by sustainable weight loss progress.

Heterogeneous peer effects have potentially large implications in the weight loss context. Because weight loss can be thought of as a personal goal, there are often peers who are disproportionately more instrumental or focal in affecting the ability or motivation to reach the goal (e.g., Fitzsimons and Fishbach 2010). For example, information disclosure about (relative) performance likely has an impact on motivation (e.g., Lockwood et al. 2002 and Karlsson et al. 2009). The weight loss program then has to decide what information about peer performance should be disclosed. If we think of the weight loss program as a form of health education, then past insights in education and psychology would suggest that motivation is delicate and quite sensitive to social comparison (e.g., Blanton et al. 1999 and Rogers and Feller 2016); furthermore, the fact that individuals can make either upward or downward comparisons with others would suggest the possibility that social comparisons may be *heterogeneous* (e.g., Buunk and Gibbons 2007).

For our empirical analysis, we are able to track each participant's weight loss progress at a high frequency for more than a million users as well as their group meeting attendance. At these meetings, participants weigh in, interact with other weight loss participants, and consult with a weight loss mentor. With these data, we investigate the impact that peer weight loss has on an individual's weight loss success. Based on a variant of the standard linear-in-means peer effect framework (Manski 1993, Brock and Durlauf 2001), we allow the peer effect to be heterogeneous across performance groups by categorizing peers at a given meeting as *best*, *average*, and *worst* performers (relative to those attending the same meeting).

A few key findings emerge. Our estimates show that the average weight loss among peers has a *negative* (i.e., discouraging) effect on an individual's own future weight loss. In contrast, we find that weight loss of the top performer has a *positive* (i.e., encouraging) effect on an individual's own future weight loss. Such findings have implications on how weight loss program employees at the meetings promote the past successes of their participants: the successes among average participants may act as a discouraging benchmark that roughly one-half of the participants will fail to reach, whereas the successes among top performers may act as an encouraging target that does not alienate as many of the participants. Furthermore, we show that our results are robust to potential issues related to selection into meetings, endogenous peer outcomes, individual unobserved heterogeneity, lagged dependent variables, and contextual effects.[1] Based on our estimates, we later discuss implications of our findings on meeting design for the commercial weight loss program in terms of *content* and *composition*. Regarding the content, the meeting leaders can, for example, use the weight loss successes of top performers to provide inspiration to the group and perhaps avoid using the overall group's success as the benchmark. Moreover, the weight loss program can design composition of groups of meeting participants that would maximize the encouraging effects of top performers and minimize the discouraging effects of average performers.

This study is related to past work that aims to identify heterogeneous peer effects. In particular, marketing research has shown that the strength of peer effects may differ depending on the peers' spatial proximity (e.g., Bell and Song 2007, Manchanda et al. 2008, Choi et al. 2010, Bollinger and Gillingham 2012, and Gardete 2015), observable physical characteristics (e.g., McFerran et al. 2010a, b; and Park and Manchanda 2014), intragroup relationship (e.g., Yang et al. 2006 and Narayan et al. 2011), and level of opinion leadership or network tie strength (e.g., Godes and Mayzlin 2009, Nair et al. 2010, Iyengar et al. 2011, and Aral and Walker 2014). The aforementioned work in marketing has studied effects of heterogeneous peer *actions* under the context of product, service, technology, and media consumption. In contrast, we are studying the effect of heterogeneous peer *outcomes* in the form of their past weight loss performance. We believe that our empirical context is uniquely well suited to help us identify encouraging role models, because the peer outcomes are a reflection of their weight loss abilities and efforts, which brings us to the second stream of literature to which our work is related.

In social psychology, researchers have investigated the impact of social comparisons with high-performing peers on self-evaluation. Some notable examples include Brewer and Weber (1994) and Pelham and Wachsmuth (1995). Collectively, these studies have shown that top performers can be either encouraging or discouraging. For example, a top performer may help provide additional motivation to achieve similar accomplishments; however, top performers may be demoralizing and lead individuals to think that their achievements are inadequate. Taken together, the fact that behaviorally top performers can be either encouraging or discouraging provides further justification that the impact of top performers remains an important empirical question. This past work has largely been confined to behavioral experiments, and therefore, we complement this literature by providing insights using a very large data set from a large commercial weight loss company. Distinguishing qualities of our data set include rich variation in meeting attendance along with the distribution of peer performance from one meeting to the next; we believe that such data qualities would be difficult to achieve in a laboratory setting.

This paper proceeds with the following structure. We first provide a detailed description of the empirical setting in Section 2, along with information about key data variation in meeting composition and peer outcomes. Our empirical analysis of heterogeneous peer effects is presented in Section 3, where we first present our empirical and identification strategy followed by a discussion of our main findings, robustness checks, and exploration of moderating effects. We then conclude in Section 4 with a brief discussion of managerial implications and future research possibilities related to our study.

2. Empirical Setting

2.1. Details About Weight Loss Program

Our analysis uses data from a large national weight loss program with nearly 2 million participants. The weight loss program is based in the United States, and it generated about $1.7 billion in revenue during 2013. Unlike some of the other popular diet programs, the weight loss program that we study does not explicitly restrict certain food groups (i.e., carbohydrates, fat, sugar, or protein). Instead, they adopt a calorie budgeting system, which gives participants the freedom to eat any type of food, provided that they do not exceed their allowed calorie budget (which may increase with exercise). A unique feature of the weight loss program is that participants attend meetings and interact with other participants. Furthermore, this program's efficacy has been validated via numerous scientific and independently conducted studies.

In-person group meetings are an important component of the weight loss program. In addition to keeping track of weight loss progress, individuals have an opportunity to interact with their peers and group mentors. To get more information about the meetings, we reached out to company representatives both via phone and in person. During a call to the weight loss program's headquarters on July 19, 2016, one of the authors asked about what activities occur during each meeting, and the membership sales representative said that "sharing of experiences with other members" is the primary and critical purpose of the meeting. There may also be discussions about weekly topics, but in general, the purpose is to allow members to be inspired and hopefully benefit from the experiences and successes of others. Meetings are typically 30 minutes long: the first 10 minutes are used by the weight loss mentor to discuss general tips about healthy lifestyles, and the remaining 20 minutes are normally allowed for social interactions. It is common to go around the room to give every participant an opportunity to share his or her weight loss experience in the past weeks or so. Virtually all participants are voluntarily transparent with one another about specifics of their weight loss progress (i.e., changes in weight and things that did and did not work for weight loss). Furthermore, there are no systematic efforts (during the period that we study) to showcase the successes of certain individuals in the group. That is, a participant in the meeting is exposed to the entire distribution of peer outcomes. On November 29, 2016, one of the authors was given permission to attend a meeting, and his observations are consistent with the details provided during the conversation with the membership sales representative.

2.2. Descriptive Patterns in the Data

2.2.1. Weight Loss. To see what a typical weight loss participant looks like, Table 1 provides the summary statistics for our sample. From this table, we see that a typical weight loss participant is about 85 kg, 65 inches, 51 years old, and female. Note that the average weight for an American female over 20 years old is about 75 kg according to the Centers for Disease Control and Prevention (CDC). Furthermore, the average body mass index (BMI) in our sample is a bit over 31, whereas a healthy BMI ranges from 18.5 to 24.9. Finally, we also observe how far an individual's weight is from their long-term weight loss goal, which was determined on joining the program.

Because weight loss is the main outcome of interest, we provide details about weight loss dynamics. We see that, from one meeting to the next, weight loss per day is on average 0.04 kg, which is considered to be a healthy weight loss rate according to the CDC guidelines, despite it seeming small. Furthermore, we can explore descriptive patterns of dynamics and seasonality in weight loss. From Figure 1, it seems that the amount of daily weight loss is largest in January and February and trends downward toward December. The improvement in weight loss may correspond with promotional efforts by the weight loss program around September to October.

Table 1. Summary Statistics

Variable	Mean	Standard deviation
Weight (kg)	85.89	21.41
Height (inches)	65.16	3.16
BMI	31.27	7.04
Weight loss per day (kg)	0.04	0.13
Age	54.02	17.83
Male	0.09	0.29
Distance to goal (kg)	6.25	7.03

Note. Averages and standard deviations are calculated across all meetings.

2.2.2. Meetings. Because weight loss meetings are a distinctive feature of this weight loss program, we provide some information about meeting attendance patterns (Figure 2). Weight loss participants on average attended about 11 meetings from 2012 to 2013. Meeting locations are spread out across the United States, where there are about 1,070 official meeting locations. Individuals typically attend meetings held at the same physical location (Figure 2(a)). Finally, we see from Figure 2(b) that a large proportion of participants (about 40%) attend meetings within the same zip code as where they live. Nevertheless, there is still a large fraction of participants who travel beyond their zip code to a meeting location (e.g., traveling more than 20 km to a meeting). To calculate the distance between each participant to the location of the last meeting attended, we compute geographic distances "as the crow flies" using longitude and latitude coordinates provided in the data. In terms of meeting attendance dynamics, Figure 2(c) shows that, in over one-half of the observations, less than a week separated the current and previous meeting. Furthermore, in most of the observations, less than a month separates current and previous meetings. There are some spikes in the distribution, because meetings are often held only on certain days of the week.

2.2.3. Composition of Peers and Peer Weight Loss Performance. Our empirical analysis is centered around understanding heterogeneous peer effects, and therefore, we will highlight variation in the composition of meeting attendees followed by a description of dynamics

Figure 1. Magnitude of Weight Loss Per Day (Kilograms) by the Month

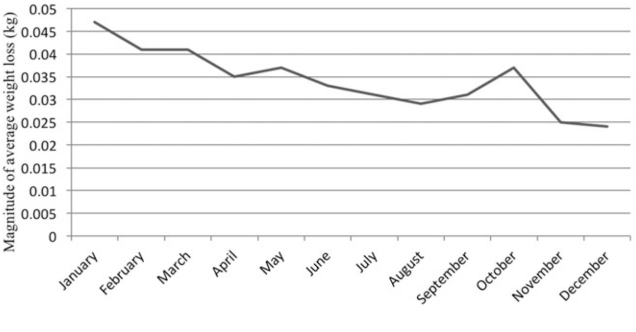
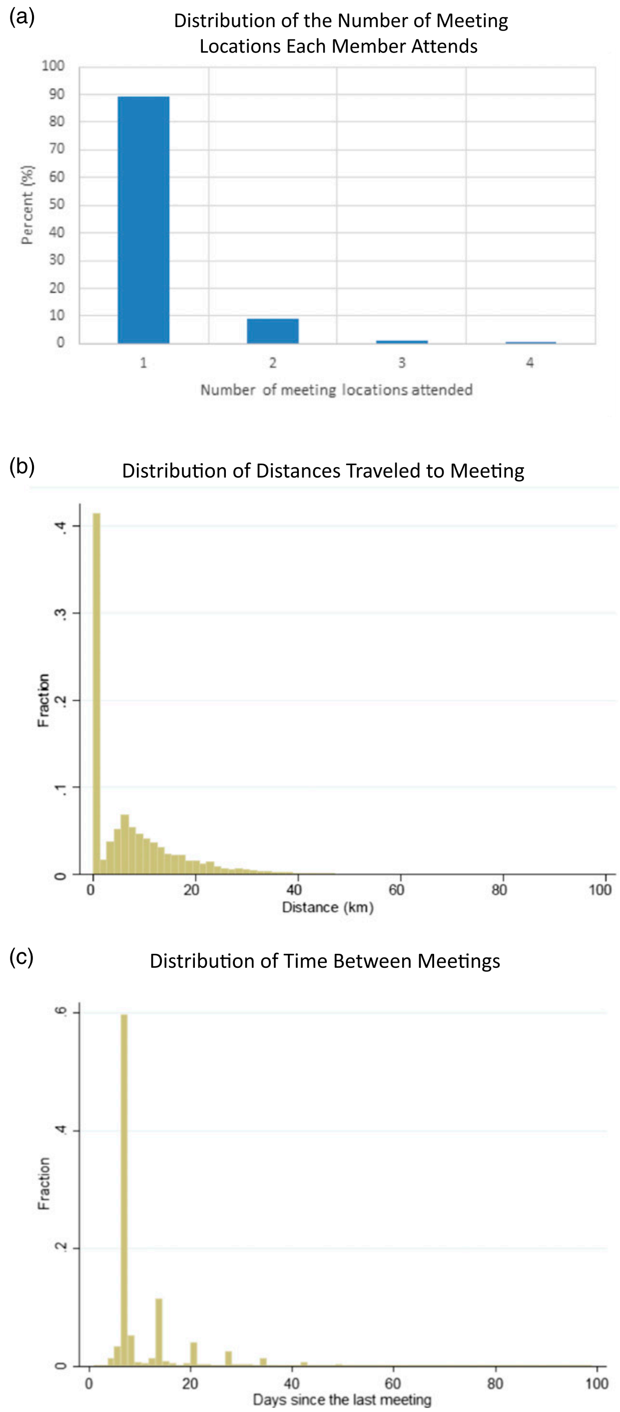


Figure 2. (Color online) Descriptive Patterns in Meeting Attendance



Notes. (a) Number of meeting locations calculated to be the number of unique locations a user has visited over the course of our data sample. (b) Distances are measured in kilometers (km), and are calculated based on longitude/latitude coordinates of the participant's home address and meeting location. (c) Time between meetings calculated as the days that separate a current and previous meeting attended by an individual.

in peer weight loss performance (Figure 3). From meeting to meeting, our data confirm that the composition of peers changes, sometimes drastically so.[2] Another way to show variation in meeting group composition dynamics is to plot the histogram for the change in number of peer participants that an individual faces from one meeting to the next. Figure 3(a) shows us the distribution summarizing changes in peer group size. This histogram shows that each individual likely faces a different set of peers across meetings. In fact, in only about 5% of the observations do we see no change in the number of peers, and in only 10% of the observations do we see a change of only one. On a similar note, we can confirm that there is sufficient turnover from one meeting to the next, such that, on average, only 27% of the peers attended the same previous meeting as an individual. Figure 3(b) shows that sizeable proportions of observations, roughly 25%, are cases in which an individual faces a completely new set of peers.

Across meetings, we also see variation in who the best performer is. An individual is the best performer in 6% of the total meetings attended. In 99% of the observations, an individual attends a group with a new top performer. More generally, there is variation in their relative ranks with respect to weight loss from one meeting to the next. Figure 3(c) provides a table that tabulates the transition matrix for *future* relative weight performance rank (as indicated by the columns) with *current* relative weight performance rank (as indicated by the rows) in meetings with 10 or more participants; akin to a heat map, we use darker shading to indicate larger values. As an example of how to interpret Figure 3(c), the top right element should be interpreted as a 5% probability that a top performer is the 20th ranked performer in his or her next visit. Figure 3 confirms that, although some best performers continue to perform well in subsequent meetings, there are a large number of observations in which relative weight performance rank changes from one meeting to the next.

2.2.4. Instruments Used for Analysis. Finally, our empirical analysis makes use of instrumental variables to address the identification issues that we outline in the next section. Table 2 summarizes the main instruments that we use for our analysis. Note that the distance variable is constructed using the physical distance between the meeting location that the participant attended during the last period and the participant's address. Furthermore, localized daily weather data are at the longitude-latitude level, and they are obtained from the National Centers for Environmental Information. These summary statistics confirm that the distance and weather conditions faced by average, bottom, and top performers are indeed different.

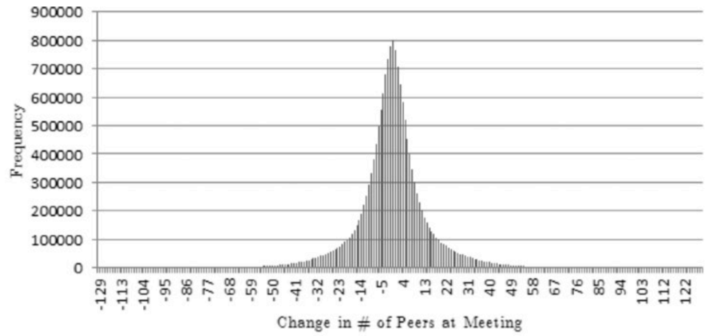
3. Empirical Analysis of Heterogeneous Peer Effects

3.1. Main Specification

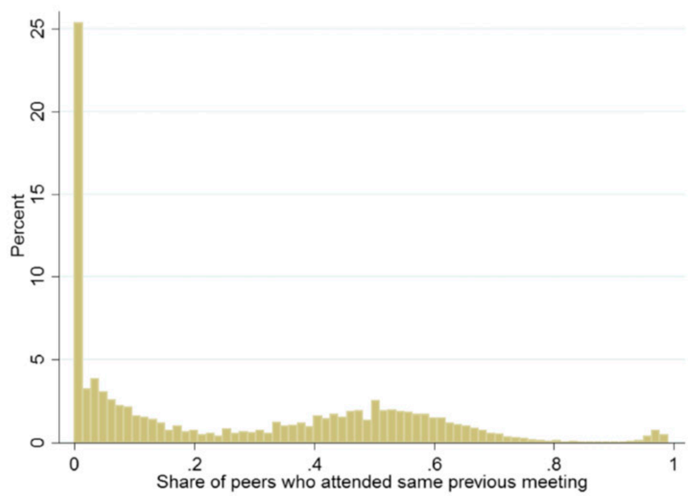
Our empirical strategy is an extension of the linear-in-means specification for peer effects (Manski 1993,

Figure 3. (Color online) Descriptive Patterns in Peer Composition

(a) Distribution of the Changes in the Number of Meeting Participants



(b) Share of Recurring Peers



(c) Dynamics in Relative Performance Rank

Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum across columns
1	0.09	0.06	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	102,314
2	0.07	0.06	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	123,896
3	0.07	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	138,090
4	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	147,905
5	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	155,091
6	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	160,670
7	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	165,869
8	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	169,020
9	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	172,922
10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	174,539
11	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	177,101
12	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	177,660
13	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	177,933
14	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	176,582
15	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	174,141
16	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	170,988
17	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	166,017
18	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	160,670
19	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	153,999
20	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	146,913

Notes. (a) Change in the number of peers is calculated based on the difference between the total number of participants at current meeting versus the number of participants in the previous meeting. (b) The share is calculated by dividing the number of peers in current meeting who were in the same previous meeting as the focal individual, with the total number of peers in the current meeting. This histogram provides distribution of these calculated shares. (c) Rows represent current weight performance rank, while columns represent future weight performance rank. Performance rank is calculated by ordering the weight loss outcomes, from best to worst. The final column adds up the total number of observations in each cell across the columns.

Table 2. Summary Statistics for Distance and Daily Weather Instruments

Instrument	Mean	Standard deviation
Distance to meeting (km)		
Average performer	22.1196	73.3447
Worst performer	24.3190	182.9587
Best performer	22.3350	169.1483
Weather instruments		
Precipitation (mm)	25.2323	70.0818
Max temperature (degrees Fahrenheit)	185.368	101.9357
Min temperature (degrees Fahrenheit)	84.4734	81.5069
Distance to meeting × min temperature		
Average performer	2,117.863	9,000.345
Worst performer	2,355.863	22,864.62
Best performer	2,129.498	21,081.1
Distance to meeting × precipitation		
Average performer	554.7244	6,013.747
Worst performer	597.5546	12,158.52
Best performer	556.8712	11,542.3
Distance to meeting × max temperature		
Average performer	4,379.324	15,697.87
Worst performer	4,852.011	40,708.42
Best performer	4,416.226	37,380.23

Note. Daily weather data are at the longitude-latitude level, and they were obtained from http://www.ncdc.noaa.gov/cdo-web.

Brock and Durlauf 2001). For a general overview of peer effects research in marketing, we refer readers to Hartmann et al. (2008). We extend this specification by incorporating more detailed information about the distribution of peer outcomes (i.e., best and worst performer outcomes), not just the average peer's performance, which then allows for these effects to be heterogeneous. The main specification that we use is described as

$$y_{it} = \alpha y_{it-1} + \gamma_1(y^{Avg}_{it-1} - y_{it-1}) + \gamma_2(y^{Worst}_{it-1} - y_{it-1}) + \gamma_3(y^{Best}_{it-1} - y_{it-1}) + \beta X_{it} + \mu_i + \mu_l + \mu_m + \varepsilon_{it}. \quad (1)$$

Here, y_{it} is the weight loss per day from meeting $t-1$ to t for individual i. Potential inertial effects are captured by α. Furthermore, peer effects are captured by $(\gamma_1, \gamma_2, \gamma_3)$, because we allow for the possibility that the difference between a peer's weight loss and i's past weight loss has an impact on i's current weight loss. The various peer outcomes are denoted by y^{Avg}_{it-1}, y^{Worst}_{it-1}, and y^{Best}_{it-1}, which capture the average, worst, and best weight loss among i's peers at a previous meeting $t-1$, respectively. The model also includes time-varying covariates of participant i in X_{it} to control for contextual effects, which contain the distance to goal, the number of others at the previous meeting, the number of days since the last meeting, and the number of days since joining the weight loss program as well as interactions between some of these variables and the peer weight loss outcomes. Instrumental variables used for our analysis are denoted by Z_{it}, which includes detailed information about each meeting participant's (i.e., individual, average performer, worst performer, and best performer) physical distance to the meeting location interacted with daily weather patterns (i.e., temperature and precipitation). Lastly, our model controls for any individual-level unobserved heterogeneity by including μ_i, location-level local unobserved heterogeneity by including μ_l, and month fixed effects by including μ_m. The month fixed effect can help control for national-level advertising and promotion campaigns.[3] We have provided a summary table with the list of key variables in Table 3 for the reader's convenience.

Table 3. Summary Table with Variable Notation and Descriptions

Notation	Description
y_{it-1}	Last period weight loss per day (kg)
y^{Avg}_{it-1}	Last period weight loss of the average-performing peer (kg)
y^{Worst}_{it-1}	Last period weight loss of the worst-performing peer (kg)
y^{Best}_{it-1}	Last period weight loss of the best-performing peer (kg)
X_{it}	Distance to goal, attendance count, experience, and relevant interactions
Z_{it}	Instruments including distance to meeting and local weather patterns
μ_i	User i fixed effect
μ_l	Location l fixed effect
μ_m	Month m fixed effect

Note. The distance variable is constructed using the physical distance between the meeting location that the participant attended during the last period and the participant's address.

Note that the main specification can be rewritten as follows:

$$y_{it} = (\alpha - \gamma_1 - \gamma_2 - \gamma_3)y_{it-1} + \gamma_1 y_{it-1}^{Avg} + \gamma_2 y_{it-1}^{Worst} + \gamma_3 y_{it-1}^{Best} + \beta X_{it} + \mu_i + \mu_l + \mu_m + \varepsilon_{it},$$

which will ultimately be our estimation equation. By letting $\tilde{\alpha} = \alpha - \gamma_1 - \gamma_2 - \gamma_3$, we can simplify the estimation equation further:

$$y_{it} = \tilde{\alpha} y_{it-1} + \gamma_1 y_{it-1}^{Avg} + \gamma_2 y_{it-1}^{Worst} + \gamma_3 y_{it-1}^{Best} + \beta X_{it} + \mu_i + \mu_l + \mu_m + \varepsilon_{it}. \quad (2)$$

3.2. Identification

There are five main challenges to identification, namely selection into meetings, endogenous peer outcomes, individual unobserved heterogeneity, lagged dependent variables, and contextual confounds. This section will provide an outline of these issues along with how we address such concerns in our empirical strategy.

3.2.1. Selection into Meetings. A primary identification concern is selection into meetings. Because each participant can choose whether to attend a meeting, such decisions may be a function of his/her past weight loss successes or failures among other factors. Therefore, changes in weight from one meeting to the next may be an artifact of individuals attending based on how much weight they had gained or lost in the past. For example, those who have experienced past successes may have a greater incentive to attend so as to gloat about their progress. We address these concerns by taking a few steps. First, we make sure to use the normalized measure of weight loss (i.e., weight loss per day). This way, weight loss measures are scaled and thus, comparable across participants; at the very least, normalization helps us eliminate the mechanical relationship between days that separate meetings and weight loss. Second, we consider a conceptual robustness test to rule out the confounding nature of selection by analyzing the sensitivity of our results to subsamples of participants based on the frequency with which they attend meetings (i.e., every month, every two weeks, or every week). If our results were largely driven by decisions to attend meetings based on how much weight they had gained or lost in the past, then these results should disappear if we focus on participants who attend at regular frequencies (i.e., every month or week). Finally, based on the intuition from our subsample analysis, we consider a more direct way to address selection biases by including the selectivity correction term of Heckman (1979) as a control function in the second-stage regression. We construct the selectivity correction term via Olsen (1980) by estimating a series of flexible linear probability models where the dependent variable is captured by a dummy that indicates whether a participant attended a meeting within a month, two weeks, or one week of the past meeting conditional on the weather and distance variables for the individual. An important advantage of using this approach (as opposed to probit) is that the normality assumption is not needed in the derivation of the estimator by Olsen (1980).

3.2.2. Endogenous Peer Outcomes. Selection into meetings will not only affect the individuals but also, the distribution of weight loss outcomes among a group of participants in a meeting. If people attend meetings to primarily show off their past successes, then the group's weight loss success will likely be skewed to the right, whereas if people attend meetings to get back on a good weight loss trajectory (after suffering some past failures), then the distribution of weight loss among peers may be skewed the opposite direction. For this reason, we need an instrumental variable that could potentially shift attendance (and thus, distribution of peer weight loss outcomes) in an exogenous manner. To construct these instruments, we make use of information about each individual's physical distance to the last meeting that they attended from their residence along with localized weather conditions around their residence. These interacted variables then offer a plausible driver for variation in meeting attendance (and thus, distribution of weight loss outcomes) among peers that is plausibly generated by exogenous factors that exclude the very selection concerns that affect both individuals and peers alike. The nice feature about these instruments is that they impact each member differently, because participants are exposed to different distance and weather conditions; this feature is especially important, because we are interested in not only the average performer's impact but also, the best and worst performers.

3.2.3. Individual Unobserved Heterogeneity. Next, there is an issue regarding individual heterogeneity. Heterogeneity is relevant, because each participant may be inherently better or worse at losing weight because of psychological or physiological reasons. To control for individual-specific features, we include individual fixed effects in the estimation, akin to recent work about peer effects in marketing (e.g., Nair et al. 2010). This approach is feasible, because our data are rich in both the cross-sectional (i.e., number of participants) and time (i.e., number of repeat observations for the same individual over time) dimensions. Furthermore, the use of individual fixed effects relies to some extent on variation in the composition of participants across meetings, which our empirical setting exhibits (Section 2). Finally, heterogeneity may be related to an inherent tendency to attend meetings, and therefore, to some extent, these fixed effects will also control for time-invariant selection into meetings.

3.2.4. Lagged Dependent Variables. An important feature to incorporate in our analysis is past weight loss (i.e., lagged dependent variable), because health habits are potentially inertial in nature. However, incorporating past weight loss will make estimation a little more complex, because the inclusion of a lagged dependent variable implies that past weight loss will be a function of unobserved factors. For example, some weight loss participants are inherently better at losing weight than others, and thus, our inferences about the inertial effects might be overestimated. For this reason, we rely on the Arellano and Bond (1991) method that makes use of lagged differences in the dependent variable as instruments for the most recent lagged term, because differencing between current and past dependent variables alone only eliminates permanent individual heterogeneity but not time-varying individual shocks; for example, some individuals may perform better at losing weight in winter than others if they enjoy winter sports more than summer sports. Given the size of our data, we are able to observe each individual over time for a large number of observations, and thus, we are able to make use of as many as six lagged differences when we explore robustness of this approach.

3.2.5. Contextual Confounds. One final source of bias may come from contextual effects. That is, there may be a common factor to which all participants at a given meeting are exposed. Some examples of these contextual factors may be if certain weight loss meeting locations provide better information (i.e., pamphlets that they hand out at the beginning of session), facilities (i.e., meetings take place in rooms with better decor), employees (i.e., more experienced meeting leaders), or services (i.e., greater range of prepared food products available to participants). We accommodate for potential contextual effects by including location-specific fixed effects to control for these common factors that can affect every participant in a meeting.

3.3. Main Results

Table 4 provides the estimates from our first-stage estimation. Table 4, columns 1–4 provide results from the first-stage linear regression of endogenous peer weight outcomes with instruments, whereas Table 4, columns 5–7 provide the results from the first-stage control function estimates for the selectivity correction term.

The first-stage results confirm that these instruments help explain some variation in the endogenous variables. For example, we see that distance has an impact on the average performers and worst performer's past weight loss. Also, rain has an impact on all of the endogenous variables. Furthermore, the minimum temperature affects the average performer and best performer's past weight loss, whereas the maximum temperature affects the average performer and worst

Table 4. First-Stage Linear Regression Results

	First-stage IV				First-stage control function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance	−0.0000392*** (0.00000614)	0.0000230* (0.00000912)	0.00000368 (0.0000122)	−0.00000211*** (0.000000523)	−0.00000942*** (0.000000962)	−0.0000164*** (0.00000147)	−0.0000398*** (0.00000204)
Precipitation	0.0000311*** (0.00000212)	0.000152*** (0.00000769)	0.0000268** (0.00000934)	−0.00000105* (0.000000425)	−0.0000141*** (0.000000781)	−0.0000209*** (0.00000119)	−0.0000241*** (0.00000166)
Temperature max	0.000116*** (0.00000374)	0.000309*** (0.0000136)	0.0000148 (0.0000165)	0.0000210*** (0.000000785)	0.000181*** (0.00000144)	0.000258*** (0.00000220)	0.000244*** (0.00000306)
Temperature min	−0.000236*** (0.00000474)	0.0000134 (0.0000171)	−0.000518*** (0.0000208)	−0.00000864*** (0.000000989)	0.000178*** (0.00000182)	0.000125*** (0.00000278)	0.0000380*** (0.00000386)
Distance × temperature min	0.000000282*** (6.33e-08)	0.00000126*** (8.68e-08)	−0.000000415*** (0.000000117)	8.38e-09 (5.41e-09)	4.47e-08*** (9.95e-09)	9.34e-08*** (1.52e-08)	0.000000140*** (2.11e-08)
Distance × precipitation	2.51e-08 (2.65e-08)	7.01e-08 (4.73e-08)	−5.29e-08 (6.06e-08)	4.69e-10 (2.43e-09)	−1.06e-08* (4.47e-09)	9.18e-09 (6.83e-09)	1.49e-09 (9.49e-09)
Distance × temperature max	−0.00000012* (5.26e-08)	−0.000000957*** (7.36e-08)	0.000000398*** (9.99e-08)	−1.80e-08*** (4.28e-09)	−1.86e-08* (7.87e-09)	−7.33e-08*** (1.20e-08)	−0.000000110*** (1.67e-08)
Constant	0.213*** (0.000597)	−1.486*** (0.00219)	1.858*** (0.00266)	0.0572*** (0.000139)	0.990*** (0.000255)	0.911*** (0.000390)	0.729*** (0.000541)
Observations	14,395,615	14,395,615	14,395,615	14,395,615	12,397,426	12,397,426	12,397,426

Notes. Columns 1–4 provide results from the first-stage linear regression of endogenous peer weight outcomes with the instruments. The first column provides the results from first-stage linear regression of average performer's past weight loss on the weather-distance instruments. Analogously, the second, third, and fourth columns provide results from first-stage linear regressions of worst performer's past weight loss, best performer's past weight loss, and individual's past weight loss per day on the weather-distance instruments, respectively. Columns 5–7 provide the results from the first-stage control function estimates for the selectivity correction term. The fifth column uses the correction term obtained from estimating the likelihood that the participant attended the current meeting within a month of the past meeting. The sixth column uses the correction term obtained from estimating the likelihood that the participant attended the current meeting within two weeks of the last meeting. The seventh column uses the correction term obtained from estimating the likelihood that the participant attended the current meeting within one week of the last meeting. Standard errors are in parentheses.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 5. Strength of the Instrumental Variables

	(1)	(2)	(3)	(4)
Univariate F statistics				
Exogenous variables with instruments	69,264	32,823	9,861	183,634
Exogenous variables	51,386	18,700	4,243	99,999
Multivariate F statistics				
Exogenous variables with instruments	3,820	24,744	18,966	31,873
Exogenous variables	1,679	1,442	1,513	1,964
R^2				
Exogenous variables with instruments	0.0379	0.0137	0.0104	0.1786
Exogenous variables	0.0097	0.0035	0.0008	0.0436

Notes. The first column provides the F statistics and R^2 from the first-stage regressions of average performer's past weight loss. Analogously, the second, third, and fourth columns provide the corresponding results from regressions of worst performer's past weight loss, best performer's past weight loss, and individual's past weight loss per day, respectively. For the multivariate F statistics, we report the weak instrument F test statistic by Sanderson and Windmeijer (2016), because there are multiple endogenous variables that are instrumented.

performer's weight loss. Finally, we can see that the interactions between weather and distance metrics have an impact on these endogenous peer outcomes. We also note that weak instruments are unlikely to be an issue, because the F statistics and R^2 markedly increase with the introduction of instruments (Table 5). Note that, in Table 5, we consider both univariate and multivariate F tests, because there are multiple endogenous variables that need to be instrumented; for the multivariate F tests, we use the approach by Sanderson and Windmeijer (2016).[4]

We also provide results from the estimates of our control function that is used to construct the selectivity correction term of Heckman (1979) (columns 5–7 in Table 4) via the method of Olsen (1980). Table 4, column 5 uses the correction term obtained from estimating the likelihood that a participant attends the current meeting within a month of the past meeting. Table 4, column 6 uses the correction term obtained from estimating the likelihood that a participant attends the current meeting within two weeks of the last meeting. Table 4, column 7 uses the correction term obtained from estimating the likelihood that a participant attends a current meeting within one week of the last meeting. These results confirm that the weather and distance metrics help explain some of the variation in the likelihood of frequent meeting attendance.

The key findings about the effect of peers on weight loss progress are found in Table 6. The online appendix provides additional robustness checks, including the conceptual test that we use to rule out biases from selection. Table 6, columns 1–3, corresponds to the correction terms obtained from estimating the likelihood that the participant attended the current meeting within a month of the past meeting, within two weeks of the last meeting, and within one week of the last meeting, respectively. For all of the specifications, we make use of the lagged instruments as suggested by Arellano and Bond (1991). Our results are invariant to how many lags are used, which provides further support that the estimates and standard errors are unlikely to be biased by any serial correlation that may exist (see the online appendix). Because we have interaction effects in the specifications, we make use of mean-centered continuous variables. Mean centering affects the interpretation of the results, in that the intercepts are more meaningful now—the inferred moderating effects reflect differences in weight loss outcomes for an individual facing average levels of individual and peer performance. Before summarizing the peer effects, we would like to point out that there are some inertial effects in weight loss. That is, an individual's past weight loss is associated with an increase in subsequent weight loss. This finding suggests potential long-run implications of interventions that affect current weight loss outcomes. Focusing the peer effects, we see in the baseline specification that weight loss for the average peer leads to individual weight gain, because a 1-kg increase in the average peer performer's weight loss is associated with an individual's decrease in weight loss by about 0.02 kg. In contrast, we see that weight loss by the top performer leads to increased individual weight loss, because a 1-kg increase in the top performer's weight loss is associated with an individual's increase in weight loss by about 0.01 kg. Although the magnitudes of these effects seem small, we note that a large number of observations (about 41%) involve participants gaining weight; therefore, any positive impact on weight loss success would be valuable to participants.

3.3.1. Discussion. Because we focus on heterogeneity in peer performance outcomes, we not only complement the past literature in marketing that has focused on other dimensions of heterogeneity (i.e., spatial proximity, observable physical characteristics, intragroup relationships, opinion leadership, and network tie strength) but also, are able to contribute to the literature about social comparison theory. In particular, the

Table 6. Second-Stage Linear Regression Results

	(1)	(2)	(3)
Last period weight loss per day	0.0505*** (0.000721)	0.0496*** (0.000736)	0.0490*** (0.000751)
Distance to goal	0.0272*** (0.0000402)	0.0272*** (0.0000403)	0.0272*** (0.0000403)
Distance to goal × weight loss per day	0.00447*** (0.00000214)	0.00447*** (0.00000214)	0.00447*** (0.00000215)
Average performer	−0.0240*** (0.000702)	−0.0234*** (0.000710)	−0.0228*** (0.000722)
Worst performer	−0.00736*** (0.000499)	−0.00679*** (0.000493)	−0.00664*** (0.000484)
Best performer	0.00928*** (0.000449)	0.00877*** (0.000444)	0.00862*** (0.000437)
Attendance count	0.000104*** (0.00000473)	0.000105*** (0.00000473)	0.000105*** (0.00000473)
Average performer × attendance count	0.000436*** (0.0000283)	0.000439*** (0.0000283)	0.000442*** (0.0000283)
Worst performer × attendance count	−0.0000834*** (0.00000606)	−0.0000835*** (0.00000605)	−0.0000837*** (0.00000605)
Best performer × attendance count	−0.0000299*** (0.00000450)	−0.0000297*** (0.00000450)	−0.0000297*** (0.00000449)
Experience	0.0118*** (0.000272)	0.0117*** (0.000272)	0.0117*** (0.000272)
Average performer × experience	0.000373*** (0.0000445)	0.000371*** (0.0000445)	0.000370*** (0.0000444)
Worst performer × experience	0.000192*** (0.0000246)	0.000192*** (0.0000245)	0.000191*** (0.0000245)
Best performer × experience	−0.000158*** (0.0000225)	−0.000157*** (0.0000225)	−0.000157*** (0.0000225)
Selection correction	−0.00729*** (0.00215)	−0.0109 *** (0.00181)	−0.0144*** (0.00197)
Constant	−0.188*** (0.00254)	−0.185*** (0.00215)	−0.184*** (0.00198)
Observations	12,376,990	12,376,990	12,376,990

Notes. The first column uses the correction term obtained from estimating the likelihood that the participant attended the current meeting within a month of the past meeting. The second column uses the correction term obtained from estimating the likelihood that the participant attended the current meeting within two weeks of the last meeting. The third column uses the correction term obtained from estimating the likelihood that the participant attended the current meeting within one week of the last meeting. Standard errors are in parentheses.

***$p < 0.001$.

discrepancy between best and average performer effects could potentially be explained by an adaptive function related to *upward* comparisons. The negative average performer effects would then be consistent with the idea that peers who perform well may cause individuals to feel inadequate and that they themselves cannot achieve such levels of performance (e.g., Rogers and Feller 2016). Consequently, individuals may attempt to respond in a defensive manner whenever someone else outperforms them. One strategy that has been alluded to in the social comparison literature is to self-handicap and choose an obviously superior peer as a comparison target (e.g., Shepperd and Taylor 1999). It then seems plausible that this self-handicapping is less effective when the comparison target is an average performer as opposed to an obviously superior top performer. By self-handicapping, individuals can exploit upward drives in their comparisons with top performers, whereas at the same time, they counteract their feelings of under-performance (relative to peers). Our findings suggest that top-performing peers provide better motivation to weight loss participants than average-performing peers, which seems consistent with the theoretical predictions about upward comparisons and self-handicapping.

In summary, the evidence of heterogeneous peer effects has direct implications on meeting design for the commercial weight loss program. There are two main dimensions of our study's managerial implications. The first dimension of meeting design that our results may impact is content. For example, the meeting leaders can use the weight loss successes of best performers to provide inspiration to the group and perhaps avoid using the average performer's success as the benchmark. By focusing attention on the top performer, the weight loss program can better motivate participants toward sustainable weight loss. The second dimension of meeting design that may be impacted by our findings is composition. The weight loss program can form groups of meeting participants that would maximize the encouraging effects of best performers and minimize the discouraging effects of average performers. By improving the perceived performance of the weight loss program via these meeting design strategies, the firm can maintain a high level of customer satisfaction and engagement.

Based on our results, we now discuss possible moderating effects, which may allow us to refine the managerial implications. These interactions will help the weight loss program determine under which contexts the peers are more or less encouraging/discouraging. The first interaction that we look at is between the peer effects and attendance count. The average performer effect seems to be slightly less negative as the group size increases, whereas the interaction between group size and the best performer effect is small in magnitude and statistically significant. An implication of this result is that, when the group size is large, announcing the successes of the average performer seems to be less detrimental to an individual's future performance. Furthermore, the second interaction investigates whether the heterogeneous peer effects vary with an individual's experience in the weight loss program. Measuring experience as the number of days that the individual has been a member of the weight loss program, we show that the average, worst, and best performer effects do not vary much with an individual's own experience, although the best performer effect is slightly smaller for individuals who are more experienced. We also tried defining experience based on the total number of meetings that the participant has attended thus far, and the results are qualitatively the same. The moderating effects for experience reveal that highlighting the successes of best performers may be slightly more effective if the group consists primarily of inexperienced attendees.

Although we focus primarily on the heterogeneous peer effects, future work could help refine further the possible mechanisms behind the inferred patterns associated with best performer peer effects. Based on the framework by Van den Bulte and Lilien (2001), one can break down various causal mechanisms behind social influence. The first possible mechanism is information transfer, such as social learning or vicarious learning. We argue that information transfer is unlikely to be a driver of the social effects, because the top performer effects do not vary much with an individual's own experience. The second possible mechanism is performance network effect. Based on how weight loss programs work, it seems unlikely that one peer's weight loss will lead to a direct physical benefit to those attending the same meeting. The third possible mechanism is normative pressure. We believe that this mechanism is an unlikely driver behind the peer effects, because the meeting attendees are acquaintances with one another, and thus, approval among peers may not be as valuable as in cases in which members of a group are actually friends; however, a limitation of this argument is that descriptive norms may have an impact even if members in the group are not friends with one another (e.g., Cialdini et al. 1990), such that norms are defined by what is typical or normal (i.e., what most people do). Finally, the remaining mechanism is competitive concern. We believe that this mechanism may potentially fit with our empirical findings in that the discouraging average peer effect is dampened by the number of peers attending the meeting. In summary, the main effects as well as their interactions with various proxies suggest that social comparisons play a role in the peer effects. Given the resemblance between social comparisons and competitive concerns, we speculate that competitive concerns would be a mechanism that fits best with our empirical findings, although future work is needed to confirm that this is indeed the case.

4. Conclusion

Our study investigates the role of social interactions in inducing healthier behavior. We infer heterogeneous peer effects using data from a large commercial weight loss program. The findings indicate that, although the weight loss among average peers does not lead to individual weight loss, weight loss among best-performing peers has a positive impact on weight loss progress. In summary, our research suggests opportunities to improve the design of meetings by highlighting the best performer's successes (i.e., meeting content) or by forming groups that minimize the discouraging average performer's effect while maximizing the encouraging best performer's effect (i.e., meeting composition). Although this is beyond the scope of our study, we see potential in future work to explore analytically what the optimal composition would be.

From a health management perspective, future research could also investigate the interaction between peer effects and urgency of weight loss. Ma et al. (2013) show that consumption of healthy foods increases in response to diabetes diagnosis, and therefore, the adoption of healthful behavior seems to be affected by medical conditions. It would be interesting to see if the encouraging top performer effects are particularly helpful at motivating those who are in greatest need of losing weight in a short amount of time. Because weight maintenance is a key preventative measure against diabetes, such a finding would have health implications above and beyond the specific weight loss context that we study.

Finally, our research insights can be applied to scenarios well beyond weight management. For example, some contexts in which identifying the ideal role model may be important include sustainable technology diffusion and sales force motivation as well as education design. In the adoption of solar panel technologies (e.g., Bollinger and Gillingham 2012 and Kraft-Todd et. al. 2017), one could explore the role of leaders in a community in foster adoption across households. To augment the sales force control systems (Cravens et. al. 1993), our findings may suggest which employees a company should highlight to motivate others. For this reason, we see our paper's insights as being complementary with Mas and Moretti (2009) and Chan et al. (2014), because they provide evidence of peer effects in sales productivity. Similarly, in a classroom setting (Imberman et al. 2012), teachers can highlight the successes of top performers rather than the class as a whole to motivate students. Furthermore, the increasing role of gamification and social interactions in many mobile applications (Hofacker et. al. 2016) may yield fruitful settings to study who and how peer successes should be highlighted.

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Endnotes

[1] To address issues about selection and endogeneity, we make use of a combination of instrumental variables and selection correction (Olsen 1980). The instrumental variables are constructed using detailed information about each participant's physical distance to the meeting locations along with location-specific weather patterns (i.e., temperature and precipitation). Furthermore, selection correction is implemented by including a control function.

[2] On average, nearly 26,000 participants will pass by a particular location during our sample, and each meeting would consist of only 0.2% of this entire pool of potential attendees. Furthermore, each location holds on average about 94 meetings per month (or about three meetings per day). The weight loss company offers many meeting time options to accommodate for peoples' varying schedules.

[3] Based on our conversations with company representatives in June 2014, the marketing activities were not targeted toward individuals, specific meetings, or locations. Therefore, a time dummy would be sufficient as a control for the marketing intensity.

[4] We refer the reader to Leeflang et al. (2015) for more details about the suggested tests of instrumental variable strength.

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