



Canadian Centre for Health Economics
Centre canadien en économie de la santé

Working Paper Series
Document de travail de la série

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SOCIAL INTERACTIONS IN A WEIGHT LOSS
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Working Paper No: 170001

www.canadiancentreforhealthconomics.ca

January, 2017

Canadian Centre for Health Economics
Centre canadien en économie de la santé
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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 and sustainable lifestyles. Our analysis revolves around one of the largest and most extensive databases about weight loss, which contains well over 10 million observations that track individual participants’ meeting attendance and progress in a large national weight loss program. A few key findings emerge. First, while higher weight loss among average performing peers leads to lower future weight loss for an individual, the effect of the top weight loss performer among peers leads to greater future weight loss for that same individual. Second, the discouraging effects from average peers and encouraging effects from top performing peers are magnified for individuals who struggled with weight loss in the past. Third, the encouraging effect of top performers has a long-run impact on an individual’s weight loss success. Finally, we provide suggestive evidence that the discrepancy between the top and average performer effects is not likely an artifact of salience or informativeness of top performers, but instead, driven by its positive impact on the motivation to accomplish weight loss goals. Given our empirical findings, we discuss managerial implications on meeting design.

Keywords: big data; customer development; customer relationship management; healthy and sustainable living; subscription services; weight management

*This project benefited from helpful discussions with conference and seminar participants at the McGill Desautels Faculty of Management, Marketing Science Conference on Health, University of Alberta, McGill Centre for the Convergence of Health and Economics Consumer Behavior Webinar, Yale School of Management, and Yale Human Neuroscience Lab, as well as Rahi Aboutk, Kusum Ailawadi, Francesco Amodio, Neeraj Arora, David Buckeridge, Tat Chan, Hai Che, Nicholas Christakis, Laurette Dubè, Liran Einav, Gautam Gowrisankaran, Linda Hagen, Gerald Häubl, Mitchell Hoffman, Raghuram Iyengar, Sandra Laporte, Peter Popkowski Leszczyc, Yu Ma, Puneet Manchanda, Tanya Mark, Brent McFerran, Saurabh Mishra, Ashesh Mukherjee, Sridhar Narayanan, Oded Netzer, Yeşim Orhun, Margarita Pivovarova, John Pracejus, Brian Rubineau, Juan Serpa, K. Sudhir, Michael Tsang, Ishani Tewari, Kangkang Wang, Chuck Weinberg, and Sunghwan Yi

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1 Introduction

Healthy and sustainable lifestyles are currently at the top of mind for customers and firms alike.¹ In addition to direct intervention (e.g., Karmarkar and Bollinger, 2014; Charness and Gneezy, 2009; Hagen, Krishna, and McFerran, 2016; Khan, Misra, and Singh, 2015; Walsh, 2014), such lifestyles may in fact propagate throughout a social network via interactions and peer effects, as demonstrated by increased adoption of sustainable technologies due to social pressure (e.g., Bollinger and Gillingham, 2012; Goldstein, Cialdini, and Griskevicius, 2008), as well as the numerous studies showing peer effects in health outcomes (e.g., Christakis and Fowler, 2008; Cohen-Cole and Fletcher, 2008; John and Norton, 2013; Trogdon, Nonemaker, and Pais, 2008; Shin et. al., 2014). However, not all peers are alike, and thus, each peer’s impact on others within the group need not be homogeneous (e.g., Aral and Walker, 2014; Manchanda, Xie, and Youn, 2008; Nair, Manchanda, and Bhatia, 2010). Given such heterogeneity in peer effects, how should firms pick and showcase *motivational* role models in their efforts to promote healthy and sustainable 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 often play an important role in weight loss (e.g., Elfaq and Rössner, 2005; Hwang et. al., 2010; Karfopoulou et. al., 2016). Not surprisingly, the Internet is awash with inspirational weight loss role models who share details about their weight loss success (strategies). The weight loss industry in the US is particularly large and generates about \$20 billion each year from over 100 million dieters;² furthermore, weight loss mobile applications (with social components) are now commonly used,³ and in fact, mobile applications not initially designed for the purpose of weight loss are now valued by customers for their unintended health benefits.⁴ Successful weight loss can lead to improvements in energy, physical mobility, mood, self-confidence, and overall health (Klem et. al., 1997). Despite the money and attention spent towards weight loss, it remains a challenging task; in fact, weight loss attempts are often unsuccessful (Stunkard and McLaren-Hume, 1959), require high levels of exercise adherence (Pronk and Wing, 1994; Riebe et. al., 2005) and discipline about nutrition (Blair and Brodney, 1999), and may even lead to weight gain (Korkeila et. al., 1999).⁵ In light of the difficulty

¹See, for example, “Americans’ Eating Habits Take a Healthier Turn, Study Finds,” *Wall Street Journal*, January 16, 2014, as well as “It’s complicated: consumers, companies and sustainability,” *The Guardian*, July 30, 2013.

²See, for example, “100 Million Dieters, \$20 Billion: The Weight-Loss Industry by the Numbers,” *ABC News*, May 8, 2012.

³See, for example, “7 Weight Loss Apps to Help You Shed the Pounds,” *PC Magazine*, January 19, 2016.

⁴See, for example, “Why the hate-on for Pokemon Go? It’s making people healthy,” *CBC News*, August 21, 2016.

⁵While there is a common perception that weight loss is hard, there exists research demonstrating that

of weight loss, motivation plays a particularly important role as it has been shown to have an impact on self-monitoring (Webber et. al., 2010). Therefore, from a commercial weight loss program’s perspective, customer-centric program design policies aimed to shape and optimize the interactions between participants may have an implication on the level of engagement among participants as customer satisfaction and development will likely be tied to the perceived performance of the program (e.g., Anderson, Fornell, and Lehmann, 1994; Churchill and Surprenant, 1982; Kumar, Umashankar, Kim, and Bhagwat, 2014) as reflected by sustainable weight loss progress. In fact, correlational analysis by Finley et. al. (2007) demonstrated that continued enrollment in commercial weight loss programs is related to weight loss performance.

Heterogeneous peer effects are potentially relevant in the weight loss context, as recent studies in health suggest that the marginal impact that thinner peers have on obesity (or weight loss effort) is different in magnitude than that of heavier peers (e.g., Andersson and Christakis, 2016; Shakya, Christakis, and Fowler, 2015). More generally, as weight loss can be thought of as a personal goal, there are often peers that are disproportionately more instrumental or focal in affecting the ability or motivation to reach the goal (e.g., Fitzsimons and Fishbach, 2009; Garcia, Tor, and Schiff, 2013; Sampat et. al., 2014). For example, information disclosure about (relative) performance likely has an impact on motivation (e.g., Goulas and Megalokonomou, 2015; Karlsson, Loewenstein, and Seppi, 2009; Lockwood et. al., 2005). The weight loss program then has to decide what information about peer performance should be disclosed. As the weight loss program can be thought of as health education, past insights in education and psychology would suggest motivation is delicate and quite sensitive to social comparison (e.g., Blanton, Buunk, Gibbons, and Kuyper, 1999; Lockwood and Pinkus, 2007; 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). Finally, identifying ideal positive role models may be relevant in this setting as weight loss is associated with the pursuit of success, and thus invokes the regulatory focus of promotion (e.g., Lockwood, Jordan, and Kunda, 2002).

For our empirical analysis, we are able to track each participant’s weight loss progress at a nearly weekly (or even daily) level, as well as their group meeting attendance, where at these meetings, participants weigh-in, interact with other weight loss participants, and consult with a weight-loss mentor. We define peers based on identifying individuals who attend the same meetings, which is appropriate as they share the same goal of weight loss, and thus because

long-run maintenance of weight loss is feasible, albeit not a particularly common occurrence among those trying to lose weight (Wing and Phelan, 2005).

of this shared pursuit may view one another as “friends” (Huang, Broniarczyk, Zhang, and Beruchashvili, 2014); furthermore, it is plausible that even if participants in these group meetings consider one another strangers, social comparisons can be made in such settings (Morse and Gergen, 1970) as participants are encouraged (and do in fact) share their weight loss performance to other meeting attendees. We argue that our definition of peers is quite well-defined, as we observe perfectly who attends each and every meeting; other work on peer effects often rely on inferred interactions based on spatial proximity or self-reported social networks that are subject to measurement error.

Methodologically, our setting is ideal for studying heterogeneous peer effects as there is high frequency pseudo-exogenous variation in the composition of attendees at each group meeting location across time, as we see high meeting turnover along with potential randomness in attendance. The potentially random variation in group composition is important for mitigating some of the confounds associated with correlated and sorting effects (Manski, 1993); such confounds are particularly relevant in the context of identifying heterogeneous peer effects, as Andersson and Christakis (2016) show that individuals within a social network may consciously increase or decrease social interactions based on the extent to which their friends are thin or heavy. Furthermore, the large number of meeting observations for each of the 2 million participants provides us a sufficiently long panel to properly control for unobserved heterogeneity via fixed effects.⁶ Finally, our ability to identify the exact locations of each weight loss participant and meeting location yields granular travel distance and weather data that help instrument for attendance in a variety of robustness checks.

Using this data, along with dynamic panel data methods (Arellano and Bond, 1991), we investigate the impact that peer weight loss has on an individual’s weight loss success. Using a variant of the standard linear-in-means peer effect framework (Brock and Durlaf, 2001; Manski, 1993), we allow the peer effect to be heterogeneous across performance groups by categorizing peers at a given meeting as top, average, and bottom performers (relative to those attending the same meeting). Our interest is primarily in the impact of top performing peers (i.e., “Biggest Loser”) on individual outcomes and behavior.

A few key findings emerge. We first show that the average weight loss among peers has a *negative* (i.e., discouraging) effect on an individual’s own weight loss, as a standard deviation increase in the group’s average (almost) *weekly* weight loss is associated with an individual’s decrease in weight loss by about 0.17 kg. In contrast, we find that weight loss of the top performer has a disproportionately large *positive* (i.e., encouraging) effect

⁶Another advantage of observing a large number of meetings is that we are then able to track individual weight progress at a fairly high frequency. Virtually all of the existing literature about peer effects in obesity have relied on self-reported weights, which are often prone to measurement error (Villanueva, 2001).

on an individual’s own weight loss; a standard deviation increase in the top performer’s weight loss is associated with an individual’s increase in weight loss by about 0.02 kg. Given that the average weekly weight loss in our sample is about 0.21 kg, an improvement in weight loss from the “Biggest Loser” effect is roughly 10% of the overall weight loss in magnitude. Such findings have implications on how employees at the meetings promote the past successes of their participants, as the successes among average participants may act as a discouraging benchmark that roughly half of the participants will fail to reach, while the successes among top performers may act as an encouraging target that does not alienate as many of the participants. Second, we show that the average peer effects are particularly detrimental to subsequent weight loss among participants who gained weight in the previous meetings, while the top performer peer effects are particularly beneficial to such participants. Third, we demonstrate that the encouraging top performer peer effects resonate over time, which suggests long-run implications of identifying and highlighting inspirational role models; the finding that the encouraging effects of top performers persist over time is particularly important given the well-documented challenges of maintaining a healthy weight in the long-run (Stunkard and McLaren-Hume, 1959; Pronk and Wing, 1994; Korkeila et. al., 1999; Riebe et. al., 2005).

We further investigate the potential mechanism behind our empirical results. We confirm that the encouraging top performer effect and discouraging average performer effect is unlikely to be generated by the salience of peer weight loss performance (i.e., how noticeable top and average performance is); and on a similar note, we also demonstrate that the top performer effects are unlikely to be related to informativeness or helpfulness of learning from top performers. In fact, our analysis suggests that the top performer effect likely serve as motivation for an individual to achieve one’s weight loss goals.

To ensure that our results are robust, we verify that these effects are stable across alternative specifications that address endogeneity, contextual, functional form, distribution issues, and difference between gender. Endogeneity is a relevant concern as participants may choose whether or not to attend each meeting, so one of our robustness checks is to consider a specification that instruments for attendance using a combination of information about each participant’s distance to the meeting location as well as the weather that day within the region. Our results are also robust to contextual issues, as the estimates remain similar even when location and meeting dummies are included. To investigate potential sensitivity to functional form, we consider alternative constructions of the peer effect variables. Even in these alternative specifications, we still find the same qualitative patterns. We also demonstrate that our findings are robust to distributional features of the peer weight outcomes at meetings, such as skewness and variance. Consequently, we believe these robustness checks

confirm that our abstraction away from a more structural utility-based specification is reasonable for our purposes. The results of our robustness check on endogeneity and contextual factors can be found in Section 4, while the ones on functional form assumptions, distribution issues, and gender difference are in Online Appendix. We find our main results remain quantitatively similar.

1.1 Related Literature

This study is related to past work that aims to uncover heterogeneous peer effects. In particular, research has demonstrated that the strength of peer effects may differ depending on the peers' spatial proximity (e.g., Bell and Song, 2007; Bollinger and Gillingham, 2012; Choi, Hui, and Bell, 2010; Gardete, 2014; Manchanda, Xie, and Youn, 2008; Sorenson, 2006), observable physical characteristics (e.g., McFerran, Dahl, Fitzsimons, and Morales, 2010a, 2010b; Park and Manchanda, 2014), intra-group relationship (e.g., De Giorgi, Pelizzari, and Redaelli, 2010; Narayan, Rao, and Saunders, 2011; Yang, Narayan, and Assael, 2006; Yang, Zhao, Erdem, and Zhao, 2010), and level of opinion leadership or network tie strength (e.g., Aral and Walker, 2014; Godes and Mayzlin, 2009; Lin and Xu, 2015; Iyengar, Van den Bulte, and Valente, 2011; Nair, Manchanda, and Bhatia, 2010; Yoganarasimhan, 2012).⁷ 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 weight loss performance. We believe our empirical context is uniquely well-suited to help us identify encouraging role models given that the peer outcomes are a reflection of their weight loss abilities and efforts, which brings us to the second stream of literature that our work is related to.

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), Lockwood and Kunda (1997), and Pelham and Wachsmuth (1995). The findings suggest that such top performing peers may or may not be ideal role models.⁸ It is worth noting that collectively, these studies have demonstrated that top performers can either be encouraging or discouraging. For example, a top performer may help provide additional motivation to achieve similar accomplishments; but on the other hand, top performers may be demoralizing and lead individuals to think that their achievements are inadequate.⁹ Taken

⁷For a general overview of peer effects research in marketing, we refer readers to Hartmann et. al. (2008).

⁸On a related note, Buunk et. al. (1990) and Taylor and Lobel (1989) show that social comparisons can lead to either upward or downward effects on feelings about oneself.

⁹Wyma (2015) provides a number of anecdotes about the discouraging effects of social comparisons.

together, the fact that behaviorally top performers can either be 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, so we hope to complement this literature by providing insights using a very large data-set from an large commercial weight loss company. Distinguishing qualities of our data-set include rich variation in pseudo-exogenous meeting attendance along with the distribution of peer performance from one meeting to the next; we believe such data qualities would be difficult to achieve in a laboratory setting.

2 Empirical Setting

2.1 Data Description

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 generated about \$1.7 billion in revenue during 2013. Unlike some of the other popular diet programs, the weight loss program we study does not explicitly restrict certain food groups (i.e., carbohydrates, fat, sugar, etc...). 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).¹⁰ Furthermore, this program has been validated via numerous scientific and independently conducted studies.¹¹

Table 1 provides the summary statistics for our sample. From this table, we see that a typical weight loss participant is about 85 kilograms, 65 inches, 51 years old,¹² and female. Note that the average weight for an American female over 20 years old is about 75 kg according to the CDC.¹³ Furthermore, the average BMI in our sample is a bit over 31, while a healthy BMI ranges from 18.5 to 24.9.

We see that from one meeting to the next, weight loss is on average 0.2 kilograms, which is considered to be a healthy weight loss rate according to CDC guidelines. Figure 1 illustrates the distribution of weight changes, and this distribution is skewed towards losing weight. However, weight loss appears to be challenging for the participants, as a lot of the weight loss is close to 0, and in about 41% of the observations, participants gain weight from one week

¹⁰Note that we have access to the data on the points (associated with calorie budgeting), though this data is very low quality due to the self-reported nature of it.

¹¹To protect the company’s anonymity, we cannot provide detailed citations of such studies.

¹²While participants in this program may be older than the general population, it is particularly relevant and important to study weight loss in this context, as being overweight becomes a greater health threat with age (e.g., diabetes, heart disease, stroke).

¹³See, for example, <http://www.cdc.gov/nchs/fastats/body-measurements.htm>.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	N
<i>Physical characteristics</i>			
Weight	85.8896	21.4113	17,823,151
Height	65.1594	3.1552	17,823,151
BMI	31.2697	7.0432	17,823,151
Weight change	-0.2054	1.2765	16,270,056
<i>Demographic information</i>			
Age	51.8524	19.2814	1,512,958
Male	0.09823	0.2748	1,513,897
<i>Meeting characteristics</i>			
Number of meetings attended	11.099	11.089	1,605,853
Weight for average peer	86.0577	12.7403	830,510
Weight for worst performing peer	115.4977	28.1404	830,510
Weight for top performing peer	67.1173	15.5540	830,510
Weight change for average peer	-0.1987	0.9511	799,618
Weight change for worst performing peer	1.0927	2.0327	799,618
Weight change for top performing peer	-1.4364	2.1603	799,618

Figure 1: Distribution of Weight Loss

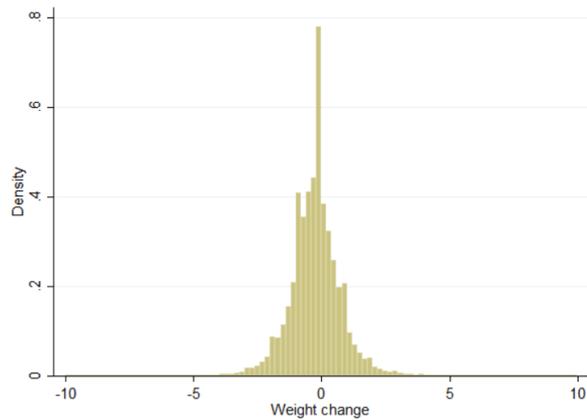
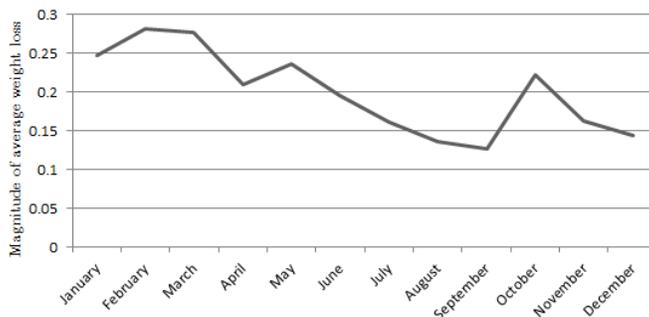


Figure 2: Magnitude of Weight Loss by the Month



to the next. Furthermore, we can explore descriptive patterns of dynamics and seasonality in weight loss. From Figure 2, it appears that the amount of weight loss is largest in January and February, and trends downwards towards December; this pattern is consistent with the notion that weight loss efforts typically weaken towards major holidays, such as Christmas (e.g., Baker and Kirschenbaum, 1998; Boutelle et. al., 1999; Helander, Wansink, and Chieh, 2016). The improvement in weight loss may correspond with promotional efforts by the weight loss program around September to October. As expected, we see that average peers have similar weight loss of 0.2 kilograms, although top performers lose nearly 2 kilograms across meetings.

Weight loss participants on average attend about 11 meetings from 2012 to 2013, as summarized in Table 1.¹⁴ Meetings are spread out across all of United States (see Figure 3); there are about 1,070 official meeting locations. Individuals typically attend meetings held at the same physical location (see Figure 4). Finally, we see from Figure 5 that a large proportion of participants, about 40%, attend meetings within the same zip code as where they live. Note that there is still a non-negligible proportion of participants who travel beyond their zip code to a meeting location; furthermore, some these participants may travel over 20 km to reach a meeting. To calculate the distance of each participant to the meeting location, we compute geographic distances (i.e., “as the crow flies”) using longitude and latitude coordinates provided in the data.

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. Although the meeting weigh-in is done privately, knowledge about each peer’s weight loss progress may diffuse within the meeting through socializing or perceptible weight changes. Sharing of experiences and outcomes are in fact

¹⁴Note that the distribution of the number of meeting attendance is skewed toward left as there are non-negligible number of users who attend a meeting only once or twice.

Figure 3: Meeting Locations Across the United States

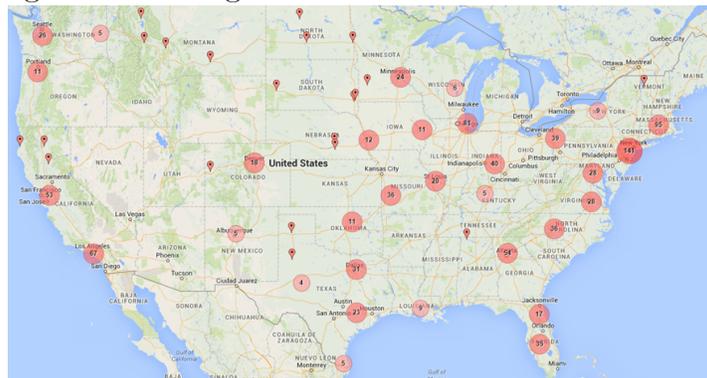


Figure 4: Distribution of the Number of Meeting Locations Each Member Attends

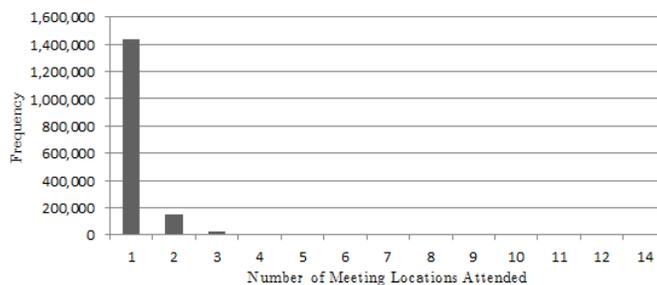


Figure 5: Distribution of Distances Traveled to Meeting

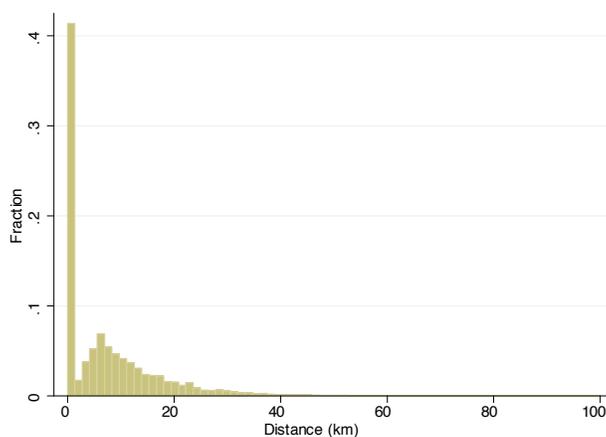
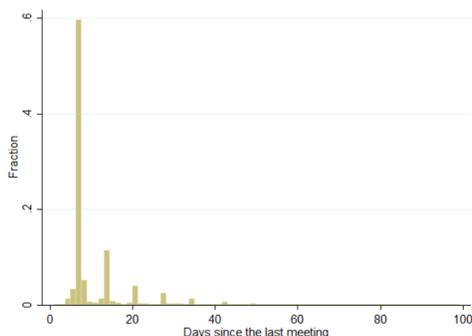


Figure 6: Distribution of Days Spaced Between Meetings



a key selling point for the meetings, as per conversations we had with the company’s sales representatives; in fact, most participants share their weight loss progress at the meetings.¹⁵ Furthermore, the weigh-ins occur before each of the meetings, so meeting participants (and perhaps mentor) are fully aware of their own weight loss progress thus far before the start of the meeting.

Based on meeting attendance patterns, we see that for a large share of observations. Figure 6 shows that in over 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 peaks in the distribution as meetings are often held only on certain days of the week. The high frequency of meetings implies that we have a large number of observations for most weight loss participants.

2.2 Meeting Composition and Peer Weight

A meeting an individual attends has on average 33 other participants, although we observe as many as 147 peers in some cases. The attendance numbers overall do change from month to month. As Figure 7 shows, attendance is highest in January at over 18 million, and moves downward towards December at around 14 million. The peak in attendance during January is consistent with the notion that many individuals center their New Year’s resolutions around weight loss, while the drop in attendance during December may be correlated with the Christmas holidays. Also, there is a slight bump in the number of new member attendance around October; this pattern is largely because of promotional offers scheduled around September and October.¹⁶ The number of meeting attendees who are new participants ranges

¹⁵We provide more specific details in the Online Appendix.

¹⁶We offer an anecdote for 2012, based on an advertising calendar sent to us directly from the company. In September and the first couple weeks of October, there was a large national offer for individuals to join for free. This offer coincided with TV advertising around the same time interval. Also, instead of a typical

Figure 7: Meeting Attendance Numbers by the Month

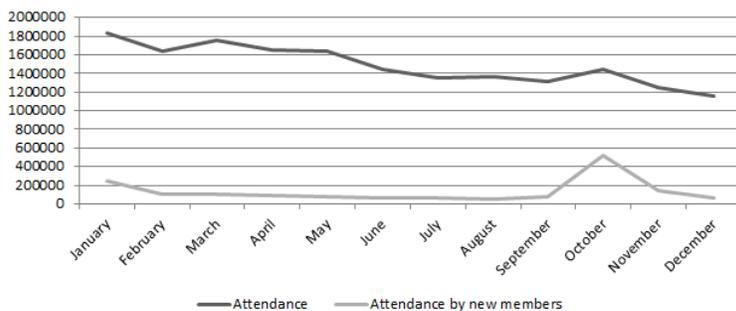
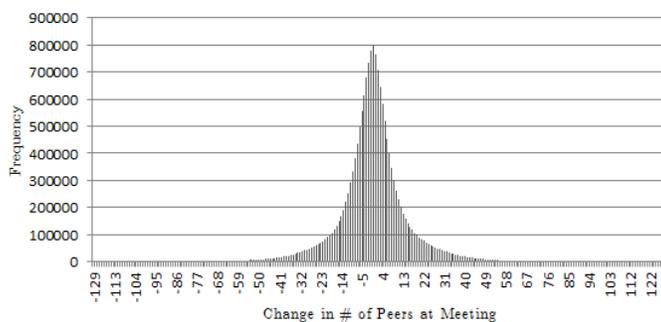


Figure 8: Distribution of the Changes in the Number of Meeting Participants



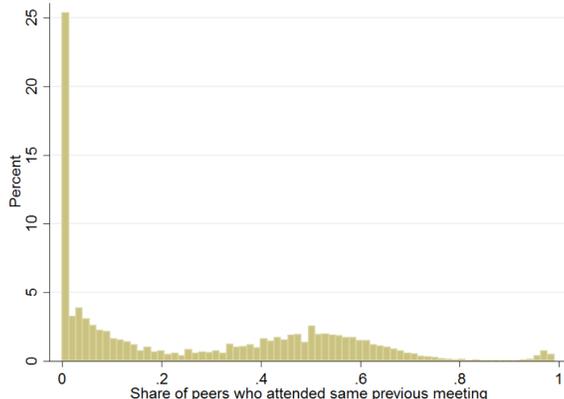
from 47,000 (in August) to 523,623 (in October).

From meeting to meeting, we do see that the composition of peers changes, sometimes drastically so. 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 has on average about 94 meetings per month (or about 3 meetings per day). The weight loss company offers many meeting time options to accommodate for peoples’ varying schedules (over time). Another way to demonstrate 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 8 shows us the distribution summarizing changes in peer group numbers. This histogram demonstrates 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 1. Furthermore, we see that the frequency of attendance number increases is about the same as the frequency

“1 month free” offer, there were email offers for more attractive “3 month free” deals to non-members during this period.

Figure 9: Share of Participants who Attended Same Previous Meeting



of attendance number decreases from one meeting to the next. 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 9 shows that a sizeable proportion of observations, roughly 25%, are cases in which an individual faces a completely new set of peers.

Across meetings, we also see variation in terms of the top performer. An individual is the “Biggest Loser” in 6% of the total meetings attended. In 99% of the observations, an individual attends a group with a new “Biggest Loser.” More generally, there is variation in their relative ranks with respect to weight loss from one meeting to the next. Figure 10 provides a table that tabulates *past* 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.¹⁷ This figure confirms that while some top 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.

Furthermore, when we look at the changes in the identity of top performers, we see that changes in the group composition are associated with increases in the likelihood of a change in “Biggest Loser” as shown in Table 2.

We now investigate the extent to which meeting composition might be exogenous. For example, we wish to rule out that high and low performers are persistently grouped with peers of the same (or different) level of performance. We explore the possibility of strategic group formation by first grouping individuals into high performance and low performance

¹⁷For a simpler illustration, we have only focused on tabulating rank dynamics among those who ranked 10 or better.

Figure 10: Dynamics in Relative Rank

Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	9,481	6,567	5,538	5,062	4,593	4,465	4,306	4,218	4,266	4,365	4,450	4,669	4,762	4,859	5,003	5,008	5,180	5,243	5,126	5,153
2	9,129	7,556	6,794	6,188	5,975	5,822	5,565	5,638	5,735	5,694	5,763	5,850	6,038	6,065	6,201	6,130	6,219	5,933	5,904	5,697
3	9,148	8,302	7,655	7,139	6,932	6,669	6,606	6,651	6,427	6,661	6,702	6,742	6,681	6,852	6,681	6,713	6,593	6,492	6,354	6,090
4	8,938	8,395	8,013	7,835	7,522	7,254	7,298	7,298	7,284	7,352	7,229	7,327	7,433	7,343	7,226	7,177	7,024	6,883	6,673	6,401
5	8,801	8,702	8,283	8,098	8,059	7,976	7,921	7,724	7,977	7,646	7,908	7,791	7,712	7,770	7,462	7,525	7,322	7,106	6,834	6,474
6	8,862	8,518	8,579	8,489	8,439	8,268	8,199	8,375	8,142	8,069	8,299	8,090	8,175	8,092	8,027	7,801	7,452	7,214	6,894	6,686
7	8,761	8,822	8,620	8,742	8,737	8,578	8,715	8,579	8,709	8,688	8,657	8,699	8,435	8,227	8,136	7,874	7,698	7,445	7,016	6,731
8	8,307	8,657	8,881	9,009	8,897	8,937	9,140	8,855	8,999	8,763	8,884	8,820	8,758	8,414	8,238	8,152	7,764	7,527	7,059	6,959
9	8,264	8,684	9,026	9,057	9,131	9,273	9,095	9,200	9,253	9,186	9,185	9,136	8,941	8,788	8,545	8,302	7,874	7,742	7,209	7,031
10	7,961	8,698	8,883	9,100	9,201	9,049	9,347	9,567	9,435	9,487	9,452	9,217	9,042	8,935	8,707	8,456	7,969	7,710	7,366	6,957
11	7,944	8,802	8,905	9,215	9,306	9,477	9,530	9,462	9,639	9,699	9,627	9,474	9,100	9,229	8,898	8,443	8,167	7,730	7,402	7,052
12	7,725	8,611	9,029	9,248	9,460	9,511	9,557	9,517	9,719	9,471	9,564	9,476	9,309	9,164	8,887	8,641	8,321	7,904	7,533	7,013
13	7,879	8,553	8,858	9,133	9,373	9,488	9,558	9,691	9,848	9,686	9,528	9,701	9,154	9,186	8,918	8,552	8,183	8,021	7,559	7,064
14	7,591	8,424	8,760	9,003	9,255	9,350	9,491	9,474	9,573	9,613	9,584	9,420	9,391	9,170	8,849	8,580	8,336	8,048	7,585	7,085
15	7,545	8,212	8,623	8,876	9,119	9,103	9,509	9,414	9,379	9,334	9,503	9,396	9,172	9,084	8,739	8,462	8,327	7,790	7,379	7,175
16	7,321	7,968	8,567	8,746	9,064	9,066	9,004	9,084	9,246	9,216	9,361	8,907	8,975	8,821	8,741	8,328	8,189	7,737	7,433	7,214
17	7,385	7,762	8,078	8,320	8,595	8,662	8,879	9,086	9,010	8,840	8,886	8,762	8,897	8,560	8,485	8,089	7,924	7,543	7,317	6,937
18	7,000	7,562	7,877	8,207	8,377	8,482	8,396	8,597	8,592	8,488	8,553	8,620	8,330	8,374	8,134	7,978	7,718	7,425	7,177	6,783
19	6,738	7,214	7,616	7,649	7,858	8,194	8,106	8,177	8,073	8,272	8,198	8,073	8,070	7,942	7,872	7,675	7,524	6,996	6,945	6,807
20	6,203	6,921	7,177	7,314	7,487	7,662	7,699	7,737	7,790	7,870	7,909	7,653	7,726	7,638	7,379	7,442	7,170	7,105	6,708	6,323

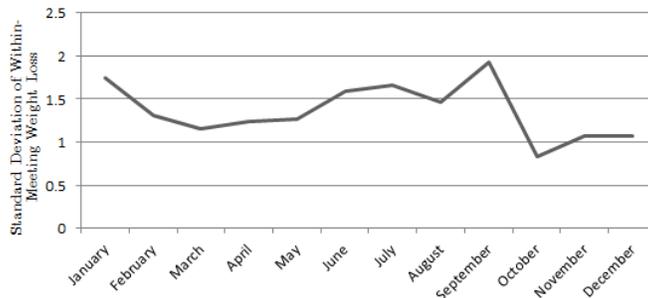
Table 2: Probability of Facing a New “Biggest Loser” as Meeting Size Changes

Change	Probability
No change	0.9893
More than 1	0.9925
More than 10	0.9950
More than 25	0.9961
More than 50	0.9998

Table 3: Suggestive Evidence of Random Group Composition

	High		Low	
	Mean	Std. Dev.	Mean	Std. Dev.
High performance peers at meeting	14	8.01	13	7.99
Low performance peers at meeting	19	11.4	21	12.4

Figure 11: Within-Meeting Standard Deviation of Weight Loss Magnitude



segments. Performance is measured based on an individual’s total weight loss. With this individual performance metric, we then do a mean split to separate individuals into the two groups. After this grouping exercise, we can then calculate the number of interactions individuals have with each performance type during a meeting.

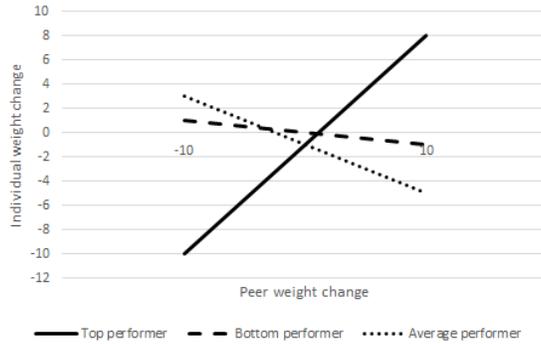
Table 3 tells us that the average number of interactions with high performance peers is very close for high and low performance individuals. We see similarities as well in terms of the number of interactions with low performance peers for high and low performance individuals. These patterns suggest potentially random variation in group composition.¹⁸

We now demonstrate that the variation in weight loss outcomes within meetings vary across time. In particular, Figure 11 shows considerable fluctuation in the within-meeting standard deviation for weight loss across the months. This figure suggests the social setting that participants interact in may not be stable over time. We will argue in the next section that such non-stationarity in the variance over time provides guidance about the appropriate peer effects econometric model to estimate.

Making use of this variation in peer weight loss, we illustrate patterns of heterogeneity in peer weight loss. Figure 12 plots the predicted weight change against the weight change among average peers (dotted line), bottom performing peers (dashed line), and top performing peers (solid line). This graph illustrates that peer weight loss (i.e., moving leftward on

¹⁸We repeat this exercise using a 3-type dichotomy (i.e., low, medium, and high performers), and the patterns are qualitatively same as the 2-type comparison.

Figure 12: Heterogeneity in the Relationship Between Individual and Peer Weight Loss



horizontal axis) is associated to individual weight loss only when peers are top performers. Interestingly, peer weight loss appears to be correlated with individual weight gain when peers are bottom and average performers. This pattern highlights potential heterogeneity in the relationship between peer and individual weight loss. More specifically, this heterogeneity identifies top performers, and not average performers, as potential *motivators* for individual weight loss; this pattern in our data foreshadows some of the key findings from our empirical analysis.

3 Peer Effects in a Weight Loss Program

3.1 Empirical Specification

To study the role of heterogeneous peer effects in weight loss, we consider a dynamic panel regression framework (Arellano and Bond, 1991). Our specification is a variant of the linear-in-means specification (Brock and Durlauf, 2001; Manski, 1993). In addition to an average peer effect, we allow for these effects to be heterogeneous (i.e., top and bottom performers).

One concern of the linear-in-means specification is that it is derived from a static Bayes-Nash game of social interactions (see, e.g., Brock and Durlauf 2001); however, when individuals interact in an unstable and non-stationary environment, the data may not be generated by a long-run static equilibrium as dictated by the Bayes-Nash game.¹⁹ Furthermore, the linear-in-means specification requires that participants are equally sensitive to all peers, and that the particular composition of peers is irrelevant; the main implication of such an assumption is that the precise allocation of peers will have no impact on the average success among participants in the weight loss program. That said, the main specification we use is

¹⁹For proofs of existence and uniqueness of equilibrium in such a game, we refer the reader to Brock and Durlauf (2001).

described as:

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

Here, $y_{it} = Weight_{it} - Weight_{it-1}$ is the change in weight from meeting $t-1$ to t for individual i . Potential momentum or forgetting effects are captured by α . Furthermore, peer effects are captured by $(\gamma_1, \gamma_2, \gamma_3)$, as we allow for the possibility that the difference between a peer's weight change and i 's past weight change has an impact on i 's current weight change. The various peer effects are denoted by z_{it-1}^{Avg} , z_{it-1}^{Worst} , and z_{it-1}^{Best} , which capture the average, worst, and best weight loss among i 's peers at a previous meeting $t-1$. The model also includes time-varying covariates of participant i in X_{it} to control for context effects. This contains the number of others at the previous meeting, number of days since the last meeting, and the number of days since joining the weight loss program. Lastly, our model controls for any individual-level unobserved heterogeneity by including μ_i , location-level local unobserved heterogeneity by μ_l , and month fixed effect by μ_m . These fixed effects are known to be crucial for ruling out selection effect and context effect and tease out peer effects.

Our main specification can be re-written as follows,

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

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

$$y_{it} = \tilde{\alpha}y_{it-1} + \beta X_{it} + \gamma_1 z_{it-1}^{Avg} + \gamma_2 z_{it-1}^{Worst} + \gamma_3 z_{it-1}^{Best} + \mu_i + \mu_l + \mu_m + \varepsilon_{it}. \quad (3)$$

3.1.1 Identification

We now discuss identification of the specification. There are two main concerns. First, are issues regarding the dynamic panel model with fixed effects. Second, are issues concerning peer effects; for these concerns, Manski (1993) summarizes the main challenges of identifying peer effects, which we will now discuss under the context of our study.

The model we use is a dynamic panel model with individual fixed effects, which inherently suffers from an endogeneity bias. To see this, we can consider a simpler version of the model:

$$y_{it} = \alpha y_{it-1} + \gamma_1 z_{it-1}^{Avg} + \mu_i + e_{it}. \quad (4)$$

After taking the first difference, we have

$$y_{it} - y_{it-1} = \alpha(y_{it-1} - y_{it-2}) + \gamma_1(z_{it-1}^{Avg} - z_{it-2}^{Avg}) + (e_{it} - e_{it-1}). \quad (5)$$

Consequently, standard OLS estimates of this model are biased as $(y_{it-1} - y_{it-2})$ and $(e_{it} - e_{it-1})$ are correlated by construction. This endogeneity problem is addressed by a method in the dynamic panel model literature as Arellano and Bond (1991). As long as e_{it} is i.i.d. across i and t , the Arellano-Bond estimator provides consistent estimates.²⁰

When identifying peer effects, Manski (1993) raises an important concern so called the reflection problem or simultaneity issue. The reflection problem is essentially the inability to separate out the endogenous peer effect and contextual effects due to a feedback loops in the endogenous variables. This issue is, however, side-stepped in our analysis as we will be employing a dynamic model; as first suggested by Manski (1993). In particular, in our model, peer interactions precede weight loss changes. A similar argument has been recently used in Bollinger and Gillingham (2012) and Chan, Li, and Pierce (2014a, 2014b).

Another important concern is related to selection of participants into meetings. The issue is that the peer effects simply reflect the tendency for certain types of participants to attend the meetings. For example, the worst performers may have a stronger incentive to attend often, as they may receive the most marginal benefits from each meeting; consequently, the peer effect on individual weight loss may be biased downward. Alternatively, the top performers may be more encouraged by their weight loss success and attend meetings more frequently; the bias in this case may be upward. We address such issues by including individual fixed effects into the estimation, which is one strategy suggested by recent work on peer effects in marketing and economics (e.g., Nair, Manchanda, and Bhatia, 2010). The richness of our data in both the cross-sectional (i.e., large number of participants) and time dimensions (i.e., large number of repeat observations for the same individual over time) makes it feasible to obtain unbiased estimates for the individual fixed effects.²¹

Another potential source of endogeneity is a correlation of error terms (i.e., e_{it}) across i . This correlation may be driven by common unobserved shock among peers, or so-called “context effect.” This correlation makes our peer effects coefficients biased as it creates a correlation between $(z_{it-1}^{Avg} - z_{it-2}^{Avg})$ and $(e_{it} - e_{it-1})$. To address this issue, we first include location fixed effects, μ_l and report the robustness results in Section 4.2. A particular meeting location may have better instruments or cleaner decoration, which motivate all

²⁰It is known that the Arrelano and Bond estimator may suffer from small sample biases. Since our data contain large N and large T , the small sample bias may not be a primary concern for us.

²¹Note that as individuals mostly attend one location, location specific heterogeneity would be captured by individual fixed effects. We however do consider robustness checks that also include location fixed effects.

participants who attend the meeting location to reduce more weight. The location fixed effects can capture those effects. We can go further to address this issue by considering use of instruments which are uncorrelated with i 's weight change, but with peers' weight change. Our instruments satisfying these conditions are distance to meeting location from each participant's residence, and local weather condition around each participant's residence. We report the results of this robustness check in Section 4.1.

Furthermore, the use of individual fixed effects still relies on the existence of variation in the composition of participants across meetings.²² Fortunately, in our setting, as shown in Section 3, there is rich variation in the meeting composition over time as confirmed in the previous section. In fact, one may assert that there is some randomness in group composition in that there does not appear to be sorting among participants based on their ability. Such variation is ultimately helpful in partially breaking the correlated effects between different members within the same meeting. Other studies have used similar strategies. For example, Chan, Li, and Pierce (2014a, 2014b) use variation in exogenous shift assignment among sales staff, while Hartmann (2010) looks at variation in groupings among golfers. In terms of similarity, our identification strategy is more closely aligned with Chan, Li, and Pierce (2014a, 2014b) and Hartmann (2010), as we do not rely on a single exogenous event to create variation in the peer group composition. Note that we do not rely solely on such variation, as our analysis also considers robustness checks using instruments for attendance based on proximity to meeting locations and localized weather patterns (i.e., precipitation, temperature).

3.1.2 Main Findings

We now summarize some of our key findings from Eq. (2) about the effect of peers on weight loss progress (Table 4). For our analysis we consider various specifications, which differ based on the explanatory variables used. All of the specifications use the lagged instruments as suggested by Arellano and Bond (1991).²³

Recall that the dependent variable is of negative value when weight loss is successful. Therefore, a positive signed coefficient for all of the estimates (with the exception of the momentum and peer effects), should be interpreted as counterproductive effects to weight loss.

We see some momentum effects in weight loss. That is, a standard deviation increase in an individual's past weight loss is associated with an increase in subsequent weight loss by

²²On a similar note, Bollinger and Gillingham (2012) mention that individual fixed effects alone are insufficient for the identification of peer effects.

²³Our results are robust to how many lags are used. For most of the lagged instruments, we find similar results. These additional robustness results are available upon request.

Table 4: Relationship Between Individual and Peer Weight Loss

	(1)	(2)	(3)	(4)	(5)
y_{it-1}	0.134*** (0.00111)	0.162*** (0.00109)	0.138*** (0.00104)	0.141*** (0.00105)	0.0676*** (0.000926)
z_{it-1}^{Avg}	-0.414*** (0.00137)	-0.446*** (0.00136)	-0.414*** (0.00131)	-0.421*** (0.00131)	-0.291*** (0.00116)
z_{it-1}^{Worst}	0.00328*** (0.000218)	0.00241*** (0.000220)	0.00362*** (0.000211)	0.00368*** (0.000212)	0.00291*** (0.000197)
z_{it-1}^{Best}	0.0132*** (0.000180)	0.0145*** (0.000181)	0.0130*** (0.000174)	0.0133*** (0.000174)	0.00878*** (0.000162)
Total number attending meeting	-0.00190*** (0.0000549)	-0.0000858 (0.0000559)	-0.000817*** (0.0000537)	-0.000156** (0.0000546)	-0.000948*** (0.0000509)
Days since joining		0.00108*** (0.00000508)	0.000439*** (0.00000495)		
Days since last meeting			0.0240*** (0.0000306)	0.0239*** (0.0000307)	0.0233*** (0.0000286)
Distance to goal					-0.409*** (0.000525)
Constant	-0.115*** (0.00106)	-0.324*** (0.00144)	-0.493*** (0.00140)	-0.454*** (0.00167)	2.137*** (0.00370)
Individual FE	X	X	X	X	X
Month FE				X	X
Observations	10457930	10457930	10457930	10457930	10457930

Standard errors in parentheses

* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$

about 0.01 kg.²⁴ This finding suggests potential long-run implications of interventions that affect current weight loss outcomes. The results also suggest that incremental weight loss is lower for individuals who have been with the program longer. Furthermore, we find that individuals who haven't attended a meeting recently do not appear to lose weight in that each day that separates one meeting to the next is associated with an increase of weight by about 0.02 kg; this result suggests that meeting attendance itself is important for weight loss success.

The presence of peers themselves appear to have an encouraging effect on weight loss, as the number of peer attendees is associated with weight loss improvements. Focusing the peer effects, we see that weight loss for the average peer leads to individual weight gain, as a standard deviation increase in the group's average weight loss is associated with an individual's decrease in weight loss by about 0.17 kg. However, we see that weight loss by the worst and top performer leads to increased individual weight loss; especially so for the top performer, as a standard deviation increase in the top performer's weight loss is associated with an individual's increase in weight loss by about 0.02 kg. Given that the average weight loss in our sample is about 0.21 kg, an improvement in weight loss from the top performer's positive spillover is roughly 10% of the overall weight loss in magnitude.²⁵

The discrepancy between top and average performer effects could potentially be explained by an adaptive function related to *upward* comparisons. That is, individuals may attempt to respond in a defensive manner whenever someone else outperforms them. One strategy that has been suggested 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 a top performer. By self-handicapping, individuals can exploit upward drives in their comparisons with top performers, while at the same time, counteract their feelings of under-performance (relative to peers). Therefore, it appears that top performing peers may provide better motivation to weight loss participants than average performing peers. Similarly, bottom performers also appear to provide motivation to individual participants. We believe this result may be linked to the notion of *downward* comparisons; that is, bottom performers may serve as a compelling example that others wish to avoid in the future (e.g., Buunk et. al., 1990; Wood and WanderZee, 1997).

²⁴Persistence in healthy habits is demonstrated in the field experiment by Acland and Levy (2013) and Charness and Gneezy (2009). Past work has suggested that one possible explanation for this persistence is habit formation.

²⁵Following the suggestions of Lin, Lucas, and Shmueli (2013), we will focus only on the magnitude of the effects (relative to the average weight loss) given that our data's size will inevitably lead to low p-values.

Table 5: Interactions Between Past Weight Gain and Peer Effects

	(1)	(2)	(3)	(4)
z_{it-1}^{Avg}	-0.229*** (0.00134)	-0.294*** (0.00122)	-0.289*** (0.00121)	-0.295*** (0.00153)
z_{it-1}^{Worst}	-0.00667*** (0.000205)	0.0264*** (0.000259)	-0.00496*** (0.000204)	0.0254*** (0.000274)
z_{it-1}^{Best}	0.00230*** (0.000166)	0.00339*** (0.000167)	-0.00963*** (0.000202)	-0.00854*** (0.000215)
Weight gain	-0.770*** (0.00197)	-0.639*** (0.00175)	-0.702*** (0.00189)	-0.595*** (0.00177)
z_{it-1}^{Avg} x Weight gain	-0.0904*** (0.00150)			-0.0221*** (0.00188)
z_{it-1}^{Worst} x Weight gain		-0.0811*** (0.000407)		-0.0772*** (0.000448)
z_{it-1}^{Best} x Weight gain			0.0320*** (0.000303)	0.0306*** (0.000346)
Constant	2.448*** (0.00419)	2.391*** (0.00413)	2.417*** (0.00416)	2.374*** (0.00412)
Observations	10457930	10457930	10457930	10457930

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tackling the Challenges of Weight Loss

For our next set of regressions, we explore interaction effects for the impact of peers in order to examine who are more likely to be affected by peers. To proceed, we repeat our baseline regressions, except that we include a dummy variable that indicates whether or not the participant *gained* weight in the previous week,²⁶ as well as interactions between this weight gain dummy with the three measures of peer effects. The results from these regressions are found in Table 5. Based on these results, we make a few observations. First, gaining weight in the previous period has a motivating effect on subsequent weight loss. Second, the interactions between the various peer effect measures with this weight gain dummy reveal that the average peer effects are less effective at motivating the participants who have been struggling in the past, while the top performer peer effects have opposite effects for those who are struggling.

Such findings are consistent with past work in psychology that demonstrate potentially

²⁶In roughly 45% of the observations, we see that the participant gained weight in the previous week.

negative effects of social comparison (e.g., Rogers and Feller, 2016). Furthermore, this finding is consistent with the notion that past peer success affects the perceived attainability of their weight loss goals, especially so when their individual performance has been markedly bad. An interesting implication of this result is that some care must be taken when highlighting past peer successes at the weight loss meetings, as a non-discriminate approach to expose everyone to such information may lead to subsequent discouragement among those who are most vulnerable. In contrast, the top performer peers appear to be establishing inspirational targets for those who are struggling with weight loss.

A specific time period in which weight loss is particularly difficult is around the holiday season, which is considered as a high-risk month for weight gain (Baker and Kirschenbaum, 1998; Boutelle et. al., 1999; Helander, Wansink, and Chieh, 2016). For our next set of analyses, we study the differential impact that peers may have during December. Individuals are particularly prone to gain weight during the holiday season as that is when they are likely to lose their self-control.²⁷ Table 6 highlights the main findings from this analysis. We first confirm that participants likely gain weight during the holiday season, or at the very least, lose less weight. Most importantly, the interaction effect illustrates that the holiday risk factor seems to be dampened by the top performer peer effect. The top performers seem particularly encouraging when an individual’s motivation is likely vulnerable to self-control issues during the holiday season. In contrast, the successes by average performers appear to increase the risks of weight gain during the holiday season.

Given that past studies have found that it is in general difficult to maintain successful weight loss in the long run (e.g., Stunkard and McLaren-Hume, 1959; Korkeila et. al., 1999), we investigate the long-run implications of the various peer effects. Achieving long-run success is particularly important as weight cycling (i.e., yo-yo dieting) has been shown to be unhealthy, especially so for women (American Health Association, 2016). In particular, we consider specifications that allow for an interaction between the peer effect and the number of days since the last meeting. One may interpret the interacted term as the peer effect’s resonance. Table 7 shows the results from these specifications. Our results highlight that the encouraging impact of top performing peers on individual weight loss resonates in the long-run, as the weight loss persists even if it has been many days since exposure to the top performer. In contrast, we find that the discouraging impact of average performing peers dampens over time, as the negative effect on weight loss diminishes in magnitude with the number of days since exposure to the average performer. The main takeaway from this finding is that highlighting the successes of top performers is a strategy that can be used for

²⁷See, for example, “Four Tips for Maintaining Your Self-Control During the Holidays,” *Kellogg Insight*, December 1, 2016.

Table 6: Interactions Between Holiday Season and Peer Effects

	(1)	(2)	(3)	(4)
z_{it-1}^{Avg}	-0.289*** (0.00117)	-0.291*** (0.00116)	-0.291*** (0.00116)	-0.287*** (0.00117)
z_{it-1}^{Worst}	0.00288*** (0.000197)	0.00297*** (0.000199)	0.00289*** (0.000197)	0.00255*** (0.000199)
z_{it-1}^{Best}	0.00892*** (0.000162)	0.00878*** (0.000162)	0.00852*** (0.000168)	0.00820*** (0.000169)
December	0.0427*** (0.00195)	0.0563*** (0.00237)	0.0575*** (0.00206)	0.0359*** (0.00275)
z_{it-1}^{Avg} x December	-0.0576*** (0.00361)			-0.105*** (0.00466)
z_{it-1}^{Worst} x December		-0.00278** (0.00104)		0.0113*** (0.00121)
z_{it-1}^{Best} x December			0.00297*** (0.000516)	0.00975*** (0.000600)
Constant	2.138*** (0.00370)	2.137*** (0.00370)	2.137*** (0.00370)	2.139*** (0.00370)
Observations	10457930	10457930	10457930	10457930

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Long-Run Implications of Peer Effects

	(1)	(2)	(3)	(4)
z_{it-1}^{Avg}	-0.292*** (0.00131)	-0.291*** (0.00116)	-0.291*** (0.00116)	-0.294*** (0.00138)
z_{it-1}^{Worst}	0.00291*** (0.000197)	0.00458*** (0.000248)	0.00293*** (0.000197)	0.00493*** (0.000265)
z_{it-1}^{Best}	0.00879*** (0.000162)	0.00877*** (0.000162)	0.00764*** (0.000204)	0.00801*** (0.000216)
Days since last meeting	0.0233*** (0.0000298)	0.0235*** (0.0000348)	0.0235*** (0.0000350)	0.0237*** (0.0000412)
Days since last meeting x z_{it-1}^{Avg}	0.0000996* (0.0000454)			0.000251*** (0.0000573)
Days since last meeting x z_{it-1}^{Worst}		-0.000146*** (0.0000132)		-0.000173*** (0.0000153)
Days since last meeting x z_{it-1}^{Best}			0.000103*** (0.0000113)	0.0000696*** (0.0000128)
Constant	2.137*** (0.00370)	2.134*** (0.00371)	2.135*** (0.00370)	2.132*** (0.00371)
Observations	10457930	10457930	10457930	10457930

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

helping participants attain sustainable weight loss.

Understanding the Mechanism A possible explanation we need to consider is the possibility that only top and bottom performers' weight loss outcomes are revealed (or salient) at the meetings. As group meeting participants can choose whether or not to share their weight loss performance, there is a possibility that only extreme cases are more noticeable than average performance. To rule out this alternative explanation, we consider a regression that interacts group size and peer effects. This specification will provide evidence in favor or against the alternative explanation. If the alternative explanation is true, then average performance should be easier to be inferred as group size decreases (i.e., need to interact with fewer participants to assess their weight loss progress).²⁸ Table 8 confirms that the average performer effect does not decrease with group size (i.e., when the average performance is less salient), and in fact, the average performer effect increases very slightly with group size. Furthermore, the interaction between group size and the top performer effect is negligible in magnitude and statistically significant, which confirms that top performers are not systematically highlighted to other participants when group size is large (i.e., when there is reason to enhance salience of past weight loss successes). Taken together, our results suggest that the salience explanation for non-positive average performer effects is unlikely to play a big role.

Another potential explanation for the top performer's positive effect on individual weight loss is that they provide helpful information and tips to other participants. To test for this explanation, we consider interactions between an individual's experience with the weight loss program - measured by number of years they have been members - and peer weight loss. The intuition behind this specification is as follows. Those who are more experienced with the program are presumably better informed about weight loss methods. Therefore, if top performers act are particularly helpful and informative, then the weight loss successes among top performers should be more (less) helpful for newer (experienced) members. Table 9 shows that there exists no evidence that more experienced members are less receptive to top performer effects.

Our previous results would suggest that the top performer effect is unlikely to be driven by salience and information factors, so in our next specification, we explore the possibility that the top performers keep their fellow peers motivated to attain their weight loss goals. To investigate this potential mechanism, we consider interactions between the peer effects and an indicator for whether a goal has *not yet* been achieved. Table 10 provides the main

²⁸Duflo and Saez (2002) also exploit group size interactions to better understand the mechanism behind the inferred peer effects.

Table 8: Test for the Saliency Effect

	(1)	(2)	(3)	(4)
z_{it-1}^{Avg}	-0.296*** (0.00121)	-0.293*** (0.00124)	-0.299*** (0.00123)	-0.316*** (0.00145)
z_{it-1}^{Worst}	0.00154*** (0.000216)	0.00462*** (0.000413)	0.00377*** (0.000201)	0.00770*** (0.000428)
z_{it-1}^{Best}	0.00748*** (0.000182)	0.00894*** (0.000166)	0.0152*** (0.000326)	0.0156*** (0.000339)
Total number attending meeting	-0.000631*** (0.0000548)	-0.000838*** (0.0000560)	-0.00134*** (0.0000538)	-0.000608*** (0.0000623)
$z_{it-1}^{Average}$ x Total number attending meeting	0.00134*** (0.0000860)			0.00203*** (0.0000903)
z_{it-1}^{Worst} x Total number attending meeting		-0.0000661*** (0.0000140)		-0.000222*** (0.0000148)
z_{it-1}^{Best} x Total number attending meeting			-0.000200*** (0.00000884)	-0.000259*** (0.00000921)
Constant	2.134*** (0.00370)	2.135*** (0.00372)	2.145*** (0.00372)	2.135*** (0.00374)
Observations	10457930	10457930	10457930	10457930

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Test for the Information Effect

	(1)	(2)	(3)	(4)
z_{it-1}^{Avg}	-0.294*** (0.00120)	-0.291*** (0.00116)	-0.291*** (0.00116)	-0.295*** (0.00122)
z_{it-1}^{Worst}	0.00292*** (0.000197)	0.00287*** (0.000204)	0.00291*** (0.000197)	0.00319*** (0.000206)
z_{it-1}^{Best}	0.00879*** (0.000162)	0.00878*** (0.000162)	0.00840*** (0.000169)	0.00871*** (0.000171)
z_{it-1}^{Avg} x Number of years member	0.000691*** (0.0000594)			0.000782*** (0.0000789)
z_{it-1}^{Worst} x Number of years member		0.00000935 (0.0000123)		-0.0000652*** (0.0000144)
z_{it-1}^{Best} x Number of years member			0.0000892*** (0.0000110)	0.0000204 (0.0000130)
Constant	2.137*** (0.00370)	2.137*** (0.00370)	2.137*** (0.00370)	2.137*** (0.00370)
Observations	10457930	10457930	10457930	10457930

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Test for Goal Attainment Motivation

	(1)	(2)	(3)	(4)
z_{it-1}^{Avg}	-0.254*** (0.00200)	-0.290*** (0.00116)	-0.291*** (0.00116)	-0.265*** (0.00242)
z_{it-1}^{Worst}	0.00277*** (0.000197)	0.0197*** (0.000409)	0.00289*** (0.000197)	0.0172*** (0.000461)
z_{it-1}^{Best}	0.00861*** (0.000162)	0.00869*** (0.000162)	0.00288*** (0.000348)	0.000843* (0.000395)
Goal not achieved	-0.0888*** (0.00248)	-0.0463*** (0.00255)	-0.0659*** (0.00255)	-0.0389*** (0.00270)
z_{it-1}^{Avg} x Goal not achieved	-0.0422*** (0.00195)			-0.0285*** (0.00251)
z_{it-1}^{Worst} x Goal not achieved		-0.0207*** (0.000439)		-0.0177*** (0.000506)
z_{it-1}^{Best} x Goal not achieved			0.00714*** (0.000374)	0.00937*** (0.000432)
Constant	2.192*** (0.00401)	2.157*** (0.00399)	2.173*** (0.00402)	2.151*** (0.00407)
Observations	10457930	10457930	10457930	10457930

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

findings from this specification. These results would suggest that the peers do have an impact on goal attainability. First note that in general, individuals tend to lose more weight (i.e., weight change is more negative) if they have not yet reached their goal, which seems intuitive. The pattern we want to emphasize is that it is only the top performers who have encouraging effects on those who have not yet achieved their weight loss goal (i.e., those who *should* be more *motivated*). In contrast, the average and worst performers are discouraging for those who have not yet reached their goal.

Implications on Meeting Design 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 top performers provide inspiration to the group, and perhaps avoid using the overall group’s success as the benchmark. By focusing attention on the top performer,

the weight loss program can address some of the key challenges of 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 top performers and minimize the discouraging effects of average performers.

Recall that the encouraging effects from top performers are persistent over time and particularly pronounced for those who are struggling. This empirical finding provides further justification to exploit the top performer’s successes (via meeting content and composition), as the positive spillovers from such peers address some of the most difficult aspects faced in weight loss; namely, weight loss is hard to sustain in the long-run, and may even lead to weight gain. To fully exploit the motivational effects from top performers, the employees leading the meetings can ensure that the top performers successes are known to everyone especially when they notice some participants who are struggling. The perceived performance of the weight loss program (i.e., customer satisfaction) would improve drastically if the encouraging top performer effects get struggling participants back on track to losing weight.

4 Robustness of Heterogeneous Peer Effects

In this section, we implement some robustness checks. Some identification issues that require additional attention include the potential endogeneity of attendance along with potential confounding contextual effects.²⁹ In general, our results hold even when such issues are addressed.

4.1 Endogeneity of Attendance and Selection

Our identification relies on member composition being somewhat random, as in Chan, Li and Pierce (2014). This assertion is largely supported by key data patterns discussed in Section 2. Moreover, we exploit the panel structure of our data set by including individual fixed effect. The individual fixed effect controls for the portion of unobserved heterogeneity that is correlated with z_{it} variables, thus dealing with endogenous peer formation. However, as the peer effects themselves may be functions of individual heterogeneity across peers, there may remain biases (Nickell, 1981). Consequently, we allow for the possibility of endogeneity by considering instruments for peer weight loss as a robustness check.³⁰ Note that since a

²⁹In the Online Appendix, we illustrate that our results are also robust to alternative constructions of the peer outcomes, issues related to the distribution of peer outcomes at each meeting, and differences across gender.

³⁰In the absence of reliable instruments, Narayanan and Nair (2012) have developed a bias-correction approach.

customer typically goes to only one meeting location (Table 4), the potential endogeneity problem we face revolves around whether or not to go to the meeting instead of which meeting location to attend, and its subsequent bias on peer weight loss.

The instruments we use are a combination of information about the participant’s physical distance to location, as well as localized weather information. For the weather data, we have information about the level of precipitation, as well as the minimum and maximum temperatures for that day. Note that the weather information is very granular (i.e., at a longitude and latitude level).³¹ The combination of distance to meeting and weather information provides additional shocks that may affect each participant uniquely. That is, each participant’s distance to meeting depends on the place of residence, which is unlikely to be highly correlated with their own weight changes as well as weight changes among other participants.³² Furthermore, the randomness that weather adds a rich time dimension, as bad weather is likely to be a stronger deterrent to attendance for those living further away.

The specification that uses these additional instruments is provided in Table 11.³³ After applying these instruments, we see that the qualitative conclusions are the same; furthermore, the F-statistics on the excluded instruments are large, which allows us to reject the null hypothesis of having weak instruments; in particular, the F-statistics from the first-stage estimation are all above 700. As before, we still see a positive inertial effect from previous weight loss. Furthermore, the average performing peer still has a negative effect on individual weight loss, while the top-performer effect remains positive.

Another issue that may materialize due to endogenous attendance is the possibility that individuals form expectations about who else may be there in future meetings. Because expectations are unobserved, we attempt to focus on sub-samples of observations in which there are no repeated interactions from one meeting to the next. For this analysis, we only use observations in which 100% of the peers an individual faces at the current meeting are completely different from those who attended the previous meeting. For such a sub-sample, we would expect participants to have fairly low expectations about interacting the same set of peers. Table 12 confirms that even in this sub-sample, our main conclusions hold for average performer and top performer peer effects.

³¹We obtain the weather data from <http://www.ncdc.noaa.gov/cdo-web>.

³²More specifically, we calculated the average of distance from each user’s residence to the meeting location, top performer’s distance from his/her residence to the meeting location, and worst performer’s one to construct instruments.

³³The reason why there are smaller number of observations is that we use more instruments and lagged variables. We find, however, that the result is robust to a different set of instruments.

Table 11: Relationship Between Individual and Peer Weight Loss with Instruments for Peer Weight Loss

	(1)
y_{it-1}	0.0542*** (0.000666)
z_{it-1}^{Avg}	-0.0123* (0.00491)
z_{it-1}^{Worst}	-0.0193*** (0.00361)
z_{it-1}^{Best}	0.0197*** (0.000322)
Distance to goal	0.184*** (0.000370)
Total number attending meeting	0.00177*** (0.000292)
Days since last meeting	0.0129*** (0.0000253)
Observations	1048814

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Relationship Between Individual and Peer Weight Loss with Sub-Sample of Participants who Interact with Completely New Set of Peers

	(1)
y_{it-1}	0.122*** (0.00236)
z_{it-1}^{Avg}	-0.382*** (0.00284)
z_{it-1}^{Worst}	0.00392*** (0.000572)
z_{it-1}^{Best}	0.0181*** (0.000487)
Distance to goal	-0.616*** (0.00161)
Total number attending meeting	0.000576*** (0.000110)
Days since last meeting	0.0219*** (0.0000515)
Observations	2574535

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Contextual Effects

Contextual effects may be relevant in our setting if certain locations are intrinsically good or bad for the weight loss participants. For example, a particular location may be led by employees who are very effective at motivating the meeting attendees. Furthermore, particular cities may exhibit certain attitudes towards healthy behavior, as it is well known that certain cities have more or less healthy residents. In our main specification, we tried to address such an unobserved common shock by including the individual fixed effect and the time fixed effect. Since most of members in our data use only one meeting location, the individual fixed effect can capture such unobserved heterogeneity. Also, any macro-level trend that influences members' weight changes can be captured by the time fixed effect.

The absence of simultaneity via our specification helps address such concerns, but in case these contextual effects are persistent, we consider a robustness check that includes city and location fixed effects. Note that as there are a large number of locations, it is not feasible to include fixed effects for each and every location, on top of individual fixed effects and time dummies. Therefore, we include fixed effects for the top 100 locations.

Table 13 confirms that even with the addition of city and location fixed effects, the signs and magnitudes of the estimates remain very close to our baseline results about individual weight loss, thus, contextual effects do not appear to be an issue.

5 Conclusion

Our study investigates the role of social interactions in inducing healthier and more sustainable behavior. We infer heterogeneous peer effects in a weight loss program. Using data from a large national weight loss program, we show that while the weight loss among average peers does not lead to individual weight loss, weight loss among top performing peers has a positive impact on weight loss progress. Furthermore, we demonstrate that the encouraging effects from top performers are especially encouraging for those who have been struggling with weight loss, while the discouraging effect from average performers is especially discouraging for this subset of participants. The positive top performer effects are also persistent over time. Finally, robustness checks confirm that our findings hold even when we allow for potential endogeneity in meeting attendance, contextual effects, alternative functional form specifications for the peer effect measures, or various types of distributions for peer performance at meetings. In summary, our research suggests opportunities to improve the design of meetings by highlighting the top performer's successes (i.e., meeting *content*), or by forming groups that minimize the discouraging average performer's effect while maximizing the

Table 13: Relationship Between Individual and Peer Weight Loss with Location Fixed Effects

	(1)
y_{it-1}	0.0676*** (0.000926)
z_{it-1}^{Avg}	-0.291*** (0.00116)
z_{it-1}^{Worst}	0.00291*** (0.000197)
z_{it-1}^{Best}	0.00878*** (0.000162)
Total number attending meeting	-0.000942** (0.0000510)
Distance to goal	-0.409*** (0.000525)
Time since joining	0.243*** (0.000514)
Time since last meeting	0.0233*** (0.0000286)
Constant	1.919*** (0.101)
Observations	12558829

Standard errors in parentheses

* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$

encouraging top 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. As Ma, Ailawadi, and Grewal (2013) demonstrate that consumption of healthy foods increase in response to diabetes diagnosis, the adoption of healthful behavior appears 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). As weight maintenance is a key preventative measure against diabetes (Diabetes Prevention Program Research Group, 2009), such a finding would have health implications above and beyond the specific weight loss context we study, as diabetes has become an epidemic on the global scale.³⁴

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³⁴See, for example, "The Global Diabetes Epidemic," *The New York Times*, April 25, 2014.

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6 Online Appendix (Not for Publication)

6.1 More Details About Meetings

During a call 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, where 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, things that did and did not work for weight loss). 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.

6.2 More Robustness Checks

6.2.1 Other Definitions of Best Performers

In this section, we conduct sensitivity analysis for the way in which our peer effect measures are constructed. Recall that we constructed z_{it-1}^{Worst} and z_{it-1}^{Best} using the worst and best peer weight loss outcomes from the previous meetings. One potential issue of using the worst and best peers in a literal sense is that they may be outliers who are not truly reflective of what bottom and top performers typically achieve.

To ensure that our results are not driven by functional form assumptions, we consider alternative specifications that construct z_{it-1}^{Worst} and z_{it-1}^{Best} using the 95%-tile and 5%-tile peers respectively; remember that since we are looking at weight loss (i.e., negative weight change), 95%-tile peers are poor performers as their weight loss is either positive or weakly negative.

Table 14 provides the specifications that use this alternative variable construction. Our findings remain qualitatively the same even with these alternative specifications. As before, the “Biggest Loser” effect is still positive. More specifically, a standard deviation change in the 95%-tile top performer is associated with an increase in weight loss of about 0.03 kg.

6.2.2 Distribution of Weight Outcomes in Meetings

Related to the functional form assumptions come the issue of the distribution with respect to peer outcomes; namely, the distribution’s skewness and variance. The distribution of peer weight loss outcomes may be skewed positively or negatively, thereby affecting the heterogeneous peer effects of interest. To ensure that skewness of weight loss outcomes creates no biases, we conduct sub-sample analysis. In particular, we consider two sub-samples. One sub-sample consists of observations in which the past peer outcomes are skewed positively,

Table 14: Relationship Between Individual and Peer Weight Loss with Alternative Peer Weight Constructions

	(1)
y_{it-1}	0.0676*** (0.000926)
z_{it-1}^{Avg}	-0.301*** (0.00128)
z_{it-1}^{Worst}	0.00488*** (0.000300)
z_{it-1}^{Best}	0.0159*** (0.000255)
Total number attending meeting	-0.00105** (0.0000501)
Distance to goal	-0.409*** (0.000525)
Time since joining	-0.000776*** (0.00000500)
Time since last meeting	0.0233*** (0.0000286)
Constant	2.144*** (0.00372)
Observations	12558829

Standard errors in parentheses
 * : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$

Table 15: Comparison of Relationship Between Individual and Peer Weight Loss Across Meetings with Positive and Negative Skewed Weight Outcomes

	Positive skew	Negative skew
y_{it-1}	0.0790*** (0.00133)	0.108*** (0.00155)
$z_{it-1}^{Average}$	-0.290*** (0.00163)	-0.317*** (0.00195)
z_{it-1}^{Worst}	-0.00174*** (0.000254)	0.0187*** (0.000361)
z_{it-1}^{Best}	0.0187*** (0.000280)	0.00491*** (0.000216)
Total number attending meeting	-0.000342*** (0.0000707)	-0.00179*** (0.0000807)
Distance to goal	-0.402*** (0.000731)	-0.395*** (0.000796)
Time since last meeting	0.0243*** (0.0000397)	0.0230*** (0.0000499)
Constant	2.114*** (0.00516)	2.022*** (0.00565)
Observations	5809230	4595267

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Comparison of Relationship Between Individual and Peer Weight Loss Across Meetings with High and Low Variance of Weight Outcomes

	(1)	(2)
	Low variance	High variance
y_{it-1}	0.0982*** (0.00158)	0.0121*** (0.00123)
$z_{it-1}^{Average}$	-0.291*** (0.00171)	-0.256*** (0.00175)
z_{it-1}^{Worst}	0.0150*** (0.000284)	-0.00372*** (0.000312)
z_{it-1}^{Best}	0.0170*** (0.000240)	0.00103*** (0.000249)
Total number attending meeting	-0.000895*** (0.0000599)	-0.00133*** (0.0000997)
Distance to goal	-0.339*** (0.000611)	-0.462*** (0.000973)
Time since last meeting	0.0227*** (0.0000363)	0.0249*** (0.0000550)
Constant	1.668*** (0.00427)	2.612*** (0.00716)
Observations	6684005	3773925

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and another sub-sample consists of observations in which the past peer outcomes are skewed negatively. To obtain the skewness measure, we calculate the sample analogue of Pearson's moment coefficient of skewness for each meeting.

Table 15 provides the results from this sub-sample analysis. Our findings remain qualitatively the same. Most importantly, the average performer effect remains negative (with a similar magnitude), and the top performer effect remains positive (albeit with a slightly smaller magnitude).

To investigate robustness of our results to the variance, we repeat a simple sub-sample exercise. The first sub-sample consists of observations in which the past peer outcomes exhibit low variance (i.e., below the average variance in sample), while the second sub-sample consists of observations in which the past peer outcomes exhibit high variance (i.e., above the average variance in sample). Table 16 displays our findings from this analysis. As before, our results do not change qualitatively. Taken together, neither the skewness nor variance in past peer outcomes are likely to bias our estimates.

Table 17: Comparison of Relationship Between Individual and Peer Weight Loss Across Genders

	(1)	(2)
	Female	Male
y_{it-1}	0.0719*** (0.000970)	0.0466*** (0.00307)
$z_{it-1}^{Average}$	-0.285*** (0.00119)	-0.358*** (0.00466)
z_{it-1}^{Worst}	0.00259*** (0.000202)	0.00702*** (0.000769)
z_{it-1}^{Best}	0.00993*** (0.000167)	0.00128* (0.000601)
Total number attending meeting	-0.000805*** (0.0000522)	-0.00212*** (0.000198)
Distance to goal	-0.399*** (0.000541)	-0.488*** (0.00197)
Time since last meeting	0.0230*** (0.0000290)	0.0270*** (0.000126)
Constant	2.000*** (0.00369)	3.536*** (0.0177)
Observations	9457105	1000825

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2.3 Gender Differences

The data contains disproportionately more females than males. To ensure that our findings are generalizable across both genders, we repeat our estimation separately for each gender. Table 17 summarizes our findings. The results confirm that the both the discouraging effect associated with average performing peers and the encouraging effect associated with top performing peers hold across the two sub-samples. Interestingly, males appear to be slightly more discouraged by relative successes among average peers and slightly less encouraged by relative successes among top performers.