Success Breeds Success: Weight Loss Dynamics in the Presence of Short-Term and Long-Term Goals*

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Abstract

We investigate the role of short-term goal achievement on long-term goal achievement under the context of weight loss. Using unique and large-scale data from a freemium mobile weight management application (Lose It!), we track the daily dynamics of weight loss across a large number of users. The application sets a salient daily budget for calories, and by comparing cases in which the user is slightly under or over-budget, we provide a causal link between short-term goal achievement and long-term outcomes such as future weight loss, achievement of goal weight, and setting of more ambitious weight loss targets. Short-term goal achievement also have implications on future customer development as staying within the daily budget leads to an increase in premium account upgrades. Furthermore, we show that the impact of short-term goal achievement varies across user segments. We later demonstrate using a dynamic regression discontinuity design that the short-term goal achievement effects persist over time, and in fact, induce users to accomplish even more ambitious short-term goals in the future. Finally, estimates from a dynamic structural model of calories management reveal that users receive positive utility from past short-term goal accomplishments, and counterfactual analysis with the estimated model quantify the long-run user benefits of various hypothetical policies that adjust the daily budget of calories.

Keywords: Big Data; Customer Development; Customer Relationship Management; Dynamic Structural Model; Freemium; Goal Achievement; Healthy Living; Mobile Application; Motivation; Regression Discontinuity; Self Control; Weight Management

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1 Introduction

Goals are now commonly used as a motivational device in the design of self-improvement applications, loyalty programs, and video games.[1] Nowhere are goals as important as they are in motivating weight loss efforts (e.g., Beruchashvili, Moisio, and Heisley, 2014; Beruchashvili and Moiso, 2013; Bagozzi, 1998; Teixeira et. al., 2004; Foster, Wadden, Vogt, and Brewer, 1997; Linde et. al., 2004) as there is suggestive evidence that people are more successful at losing weight if they are goal-focused (e.g., Conlon et. al., 2011). The use of goals is thought to be an important behavioral treatment in weight loss programs, as they will ideally reinforce or reward positive behaviors (e.g., Foster, Makris and Bailer, 2005). Theoretically, goals serve as commitment devices[2] in light of self-control issues (e.g., Bénabou and Tirole, 2004; Gul and Pesendorfer, 2001; Laibson, 1997; O'Donoghue and Rabin, 1999; Ali, 2011). An implication of some of the theory is that self-control is easier for those who are more confident about their personal will-power, and this confidence grows over time as they exercise self-control (e.g., Bénabou and Tirole, 2004), thereby making will-power self-reinforcing over time. In response to such customer needs, some mobile applications now help users achieve their fitness and weight goals, where a new feature across many of these services is the use of *goals* as a way to motivate users.[3] Those seeking to lose weight often set a target that they aspire to, and then work towards reaching this ideal weight. Some will reach their goal, but others will fail as the achievement of difficult goals require focused attention and motivation over time (e.g., Duckworth, Peterson, Matthews, and Kelly, 2007; Webber, Tate, Ward, and Bowling, 2010), as well as high levels of self-control (e.g., Toussaert, 2016).[4] Naturally, a common issue faced

[1] Goals may also help with energy conservation (Harding and Hsiaw, 2014), worker motivation (Corgnet, Gómez-Miñambres, and Hernán-González, 2015; Goerg, 2015; Goerg and Kube, 2012) and student performance (Clark, Gill, Prowse, and Rush, 2016).

[2] Financial incentives are another form of commitment mechanism, though the empirical evidence that demonstrate their effectiveness at inducing healthy behavior in the *long-run* has been mixed (e.g., Acland and Levy, 2015; Charness and Gneezy, 2009; Giné, Karlan, and Zinman, 2010; Royer, Stehr, and Sydnor, 2015).

[3] See, for example, "Top 12 Health and Fitness Apps to Get You to Your Goals in 2017" (*Forbes*, January 7, 2017).

[4] On top of these challenges, eating healthier foods can potentially nudge consumers into feeling hungrier (Finkelstein and Fishbach, 2010).

by those seeking to lose weight is that their goals tend to be unrealistic. In fact, Linde, Jeffery, Finch, and Ng (2004) show that the goal weight has very weak correlation with actual weight loss. Thus, an important design element for these mobile applications is to ensure that they provide realistic short-term targets as these goals may serve as quick motivational gains (e.g., Brown and Lahey, 2015) and may ultimately be more attainable (e.g., Harding and Hsiaw, 2014).[5] As many of these mobile applications rely on the freemium business model,[6] it seems plausible that their effectiveness at helping users achieve goals would lead to conversions towards paid premium services offered.[7] Innovation is a key driver of customer development in freemium business models (Kumar, 2014), and one specific innovation we investigate is the prevalent use of short-term goals as a way to motivate users. Research in consumer behavior and organizational theory would further motivate the use of short-term goals, as people have been shown to react positively to feelings of goal progress (e.g., Amabile and Kramer, 2011; Campbell and Warren, 2014; Koo and Fishbach, 2008).[8] However, as alluded to in Dweck and Leggett (1988), goal accomplishment need not necessarily be motivational. For example, failure can be seen as a discouraging indictment of ability (e.g., Soman and Cheema, 2004). Furthermore, if one thinks of short-term goals as sub-goals, Fishbach, Dhar, and Zhang (2006) have shown that sub-goals may potentially be counterproductive as the sense of accomplishment from sub-goal attainment may justify temporary disengagement from the long-term goal.[9] Therefore, our research aims to determine whether or not there is indeed a *causal* relationship between *short-term* goal accomplishment and *long-term* success.

We study the relationship between short-term and long-term goal accomplishment using novel data from a large-scale freemium mobile application (Lose It!). This data allows us to

[5] Weight loss professionals have long preached the importance of setting modest weight loss goals (Foster, Wadden, Vogt, and Brewer, 1997).

[6] Freemium applications are often free to download and use, but require additional fees for additional options or services. See Lee, Kumar, and Gupta (2015) for recent research about freemium design strategies.

[7] The use of goals can be seen as a form of gamification in mobile application development (Hofacker et. al., 2016).

[8] The potential long-term benefits of short-term performance goals have also been documented in education (e.g., Harackiewicz et. al., 2000) and diabetes prevention (e.g., DeWalt et. al., 2009) contexts.

[9] More generally, it research has been mixed about the impact of goal progress on goal perseverance (Garvey, 2011).

track daily patterns in weight and calories performance for well over 40,000 active users.[10] Most importantly, this application displays prominently a daily budget of calories that users are advised to adhere as a means to reach their ultimate weight loss goal. Consequently, it is very *salient* to users if they have stayed within or gone over the daily limit.[11] Variation in daily budget adherence (or violation) then helps us establish an empirical relationship between short-term goal accomplishment, in the form of daily budget adherence, and long-term goal accomplishment, in the form of reaching their ideal weight. To address potential endogeneity of calories consumption, we employ a simple regression discontinuity design[12] that exploits local variation in realized calories around the daily budget. The basic intuition for this identification approach is that cases that are just *barely* above and barely below the budget are good comparisons, as the amount of consumed food that would separate these two scenarios is quite negligible (e.g., one small green apple, one McDonald's Chicken McNugget, or two marshmallows). In fact, exogenous environmental factors (e.g., salience of food, variety of food, size of food packages and portions, stockpiling of food, and shape of food plates, glasses, and bowls) that are sometimes beyond the control of the user can easily *interfere* with one's ability to monitor exactly how much food has been consumed (e.g., Wansink, 2004; Wansink, Just, and Payne, 2009), thereby causing users to inadvertently go above the budgeted calories that they are aiming to stay within.

Our empirical analysis demonstrates that short-term goal accomplishment may indeed have a positive spillover onto long-term goal accomplishment. In particular, we show that adherence to the daily budget leads to greater weight loss in subsequent days, weeks, and even months. Furthermore, we provide suggestive evidence that the superior performance in long-term weight loss from short-term goal accomplishment may be driven by future budget

[10] Tracking calories and weight are often considered helpful components of weight loss programs (Dalcin et. al., 2015).

[11] Salience is particularly important in goal-setting scenarios (Choi, Haisley, Kurkoski, and Massey, 2016). Furthermore, these short-term goals can help reinforce implementation intentions, which could potentially act as a powerful self-regulatory tool (Gollwitzer and Brandstätter, 1997).

[12] We refer the readers to Busse, Silva-Risso, and Zettelmeyer (2006), Hartmann, Nair, and Narayanan (2011) and Narayanan and Kalyanam (2015) for recent applications of regression discontinuity design in marketing and industrial organization research.

adherence. That is, staying within the budget of calories leads to budget adherence in the next days. In addition to helping users lose weight, we demonstrate that short-term goal accomplishment can have a direct monetary benefit to the mobile application, as those who adhered to the budget are more likely to upgrade their account from a free to premium version. We later consider specifications that permit interactions between short-term goal achievement and various identifiable user characteristics, and show that different user segments react differently to past budget adherence. In particular, we show that the positive spillover from budget adherence on weight loss is most pronounced for young male users who started the program with a high BMI. Finally, using the dynamic regression discontinuity design set forth by Cellini, Ferreira, and Rothstein (2010), we illustrate empirically the dynamic patterns of the short-term goal achievement effect. In particular, this analysis shows that short-term achievement effect on future weight loss, future goal achievements (that have more challenging and ambitious daily budget of calories), and premium upgrades can resonate even after several days have passed. This finding of persistence should be of particular interest, as it suggests that users are learning about the "type of person" they are with respect to their own will-power, whereby the past successes at budget adherence serve as *reinforcing signals* about their ability to exercise self-control as implied in the theoretical framework by Bénabou and Tirole (2004). To provide additional richness to our analysis, we present a dynamic structural model that describe individual users' decisions about food and exercise calories, and estimates from this model reveal that past short-term goal accomplishments provide users positive utility. Our estimated structural model then allows us to conduct application design strategies, such as hypothetically decreasing or increasing the daily budget of calories. The counterfactual analysis reveals that users receive higher long-run values when the daily budgets are increased slightly, which suggests the motivational gains from short-run goal accomplishment outweigh the losses from slower weight loss progress. Finally, when comparing uniform and conditional policies for budget updates, we see that if the application wishes to make short-term goals progressively more challenging, it is best to target such policies towards instances in which the user has made progress towards the long-term weight loss goal.

2 Related Literature

Traditionally, the study of goals have been studied in laboratory or experimental contexts (e.g., Beruchashvili, Moisio, and Heisley, 2014; Beruchashvili and Moiso, 2013; Bagozzi, 1998; Duckworth, Peterson, Matthews, and Kelly, 2007; Teixeira et. al., 2004; Foster, Wadden, Vogt, and Brewer, 1997; Linde et. al., 2004; Toussaert, 2016; Webber, Tate, Ward, and Bowling, 2010). Our empirical framework is quite different as we are using large-scale observational data from an actual weight loss application. We argue that our approach provides additional value to the literature as our empirical setting has a number of distinct features. First, we observe the same individual daily over the course of several months; consequently, we can see a large sequence of short-term goal achievements (or failures), and of course, their progress (as measured via various measures) several months later. Second, given the amount of information we have about the users themselves, we can further dichotomize the positive short-term goal achievement effect across user segments and situations, which would be harder to do in a laboratory setting. Third, by incorporating a structural model into our analysis, we can explore *optimal* goal design strategies that the mobile application can potentially (and may in fact eventually) adopt. Finally, the actual calories consumed exhibit rich variation *locally around* the daily budget of calories, which mitigates most shortcomings in causal inference associated with observational data that lab-based studies need not worry as much about.

Customer development strategies in weight loss program design have gone largely unnoticed in marketing and economics research. To the best of our knowledge, one exception includes recent work by Uetake and Yang (2016), who study social interactions in a large national weight loss program, with the objective of identifying ideal role models that would help motivate other peers. Our paper is more focused on how motivation and confidence builds with every short-term goal that is achieved. An important difference between our setting and theirs is that because our data comes from a mobile application, we have access to perhaps highly granular information about calories and weight over time. Furthermore, the weight loss program in Uetake and Yang (2016) does not make use of short-term goals, which is the key dimension of interest in our analysis.

There is growing interest among researchers to uncover the benefits of mobile applications with health outcomes. For example, Ghose, Guo, and Li (2017) show that mobile platforms help diabetes patients in reducing blood glucose, hospital visits, and medical expenses over time. In another example, Kato-Lin, Abhishek, Downs, and Padman (2016) show that mobile-based visual diaries can encourage healthier eating habits. Moreover, van Mierlo et. al. (2015) discuss the difficulty of getting mobile application users to adhere to healthy behavior in their analysis of GOODcoins. From health and nutrition sciences, there is evidence that mobile applications that aide in self-monitoring are effective tools for weight loss (e.g., Turner-McGrievy et. al., 2013; Wharton, Johnson, Cunningham, and Sterner, 2014). Our research insights can aide in weight loss program and application development,[13] as a shortcoming that many of these services suffer from is the lack of *behavioral* strategies aimed at helping users improve goal setting, motivation, reduce stress, and assist with problem solving (e.g., Pagota et. al., 2013; Schoffman, Turner-McGrievy, Jones, and Wilcox, 2013; Tang, Abraham, Stamp and Greaves, 2015). More generally, our work complements the growing interest in finding nudges or policies that induce customers to adopt healthier lifestyles (e.g., Chan, Hamilton, and Papageorge, 2015; Chance, Gorlin, and Dhar, 2014; Cornil and Chandon, 2016; Gordon and Sun, 2015; Hagen, Krishna, and McFerran, 2016; Huang, Khwaja, and Sudhir, 2015; Khan, Misra, and Singh, 2016; Papageorge, 2016; Rao and Wang, 2017; Wansink and Chandon, 2014).

[13] Mobile fitness applications have grown in prominence, and well-designed applications have in the past been acquired for large amounts of money. See, for example, "Under Armour Acquires MyFitnessPal for $475 Million" (*Wall Street Journal*, February 4, 2015).

From a methodological perspective, our regression discontinuity design could be applied to the extensive study of loyalty program dynamics (e.g., Guo and Orhun, 2015; Hartmann and Viard, 2008; Stourm, Bradlow, and Fader, 2015; Wang, Lewis, Cryder, and Sprigg, 2016) or customer engagement in video games (e.g., Albuquerque and Nevskaya, 2012, 2014; Huang, Jasin, and Manchanda, 2016). In loyalty programs, customers often accumulate points, which can be redeemed at various thresholds. In video games, players often accumulate points that allow them to move up from one level to the next. One common feature of both loyalty programs and video games are potential discontinuities around the thresholds associated with each loyalty or game level. Therefore, future research can exploit such variation to investigate whether passing one threshold increases the likelihood of passing another threshold (or ultimately reach the highest redemption level or loyalty status). Such dynamics do not seem far-fetched, as Nunes and Drèze (2010) have shown that successful completions of rewards lead to subsequent task completions. In other words, we believe the study of loyalty programs and video games can ultimately be framed as a study of short-term and long-term goal dynamics.

3 Empirical Setting

This section describes the mobile weight loss application we study, and provides details about the unique data we use. Most importantly, using location variation around points at which the short-term goal is binding, we highlight key raw patterns in the data that suggest a potentially causal relationship between short-term and long-term goal achievement.

3.1 Mobile Weight Loss Application and Data

We use large-scale data from a freemium mobile application (Lose It!) that helps users lose weight.[14] This mobile application is among the most popular weight loss tools, and is

[14] Collectively, users have lost well over 52 million pounds using this application.

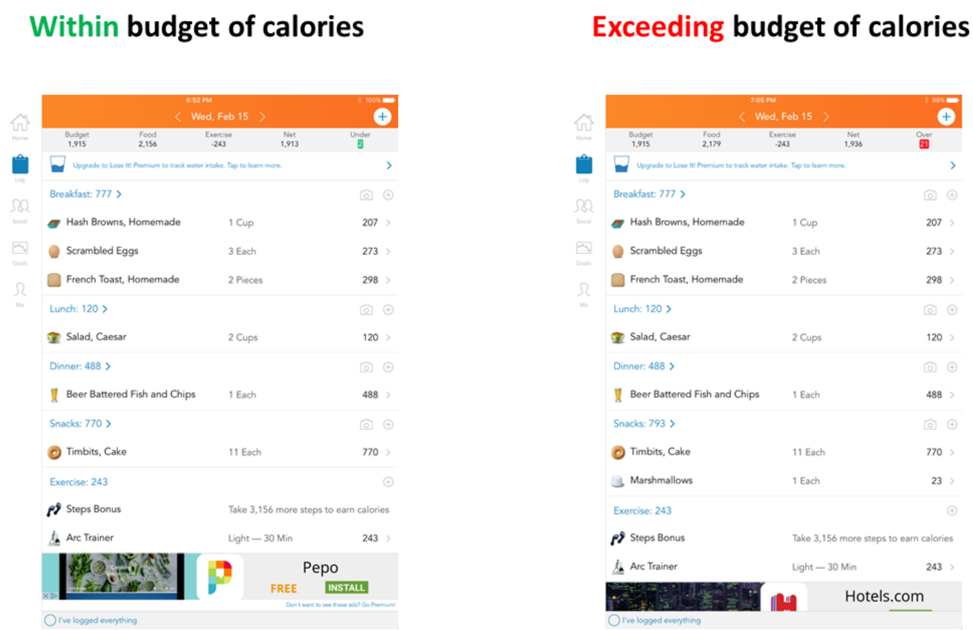
often ranked as the most effective one.[15] A sample screen-shot of the mobile application is shown in Figure 1. This application works on most smart-phones and tablets, like those running Apple iOS or Google Android. To sign up, users simply provide information about their age, gender, weight, height, goal weight, and when they would like to reach their goal weight. With this information, the application sets a daily budget of calories that users are recommended to adhere to in order to reach their goal weight.[16] After registration, users have access to the mobile application, which allows them to track their weight, calories eaten, and exercise calories. Weight and food calories are entered into the application by the user. To make it easier to keep the count of calories, users can search for foods they have eaten on the application's database,[17] and add them to their breakfast, lunch, dinner, or snack meals. The application then totals the amount of calories consumed across all of the meals. To track exercise calories, the application can be synchronized with the smart-phone to infer calories burned via a step-counter. Users can add additional activities that would further contribute towards exercise calories. With the net calories are calculated as food calories subtracted by exercise calories. The application displays very clearly how much over or under the net calories is relative to the daily budget; if users consumed less than the budget, then the difference is highlighted with a green color, while if users consumed more than the budget, then the difference is highlighted with a red color. Users can also subscribe to a premium version of this application (for a monthly fee of $3.33), which gives them access to additional features like macronutrient goal setting and tracking, nutrition insight reporting, data analysis and recommendations, meal planning, meal, plan and workout libraries, water

[15] See, for example, "11 Best Weight Loss Apps for 2017" (*GottaBeMobile*, March 1, 2017)

[16] The suggested daily budget is calculated using well-known formulae among nutritionists, that take in current and target weights, along with ideal time for reaching weight loss target. They currently are not doing any manipulations of the daily budget, though may make adjustments to further improve user engagement in the future based on our research findings.

[17] Their application uses a food database that contains well over 7 million foods, restaurant items and brands from around the world. This database was created with the aid of their in-house nutritionists. Furthermore, users can scan the food items if there are barcodes available for the items, or even take a picture (which will then lead to a list of potential foods in the picture using their advanced image recognition technology).

Figure 1: Budget Adherence versus Budget Violation in Mobile Application



tracking, customized themes, and an ad-free interface.[18]

For our analysis, we focus on the sub-sample of active users who use the weight loss mobile application daily over the course of a year, which constitutes well over 70% of the total observations. By using this sub-sample, we restrict ourselves to looking only at the regular users of this application. Furthermore, by including only those who have used the application in consecutive days, we ensure that each observation is separated by a day for a given user. This way, changes in weight over time has the same interpretation across all users. Finally, the active users that are included in our sample and the inactive users that are excluded appear quite similar in terms of their weight loss progress (i.e., no obvious patterns of selection), as the correlation between weight loss and being an active user is -0.0052, which highlights the lack of evidence that would suggest users quit using the application if they are either very successful or very unsuccessful. With this restriction, we are left with 36,245

[18] In light of the premium account option, one should think of this mobile application as being freemium.

active users who use the mobile application regularly.

Table 1: Summary Statistics for Regular Users

Variable	Mean	Std. Dev.	N
User demographics			
Age	39.655	14.091	7237756
Gender	0.338	0.473	7237880
Height	66.760	3.873	7237880
User weight			
Start weight	194.582	50.408	7237880
Current weight	184.565	46.249	7237880
Goal weight	158.962	33.821	7236902
Start BMI	30.538	6.869	7237880
Usage patterns			
Budget calories	1578.96	411.33	7237880
Food calories	801.254	845.359	7237880
Exercise calories	147.49	323.049	7237880
Premium account	0.15	0.357	7237880

Table 1 provides summary statistics for our sample. A majority of users on this application are female and have a slightly higher BMI than the recommended level when they start the program. They are on average around 40 years old, and are close to 200 pounds when they start. Their average food calories intake is around 800, while their exercise calories is around 150. Finally, we see that the average budget for calories is around 1600. Finally, we see that a sizeable proportion of users (about 15%) take advantage of the premium account option that provides additional features.

The mobile application appears to be quite effective at helping users reduce their net calories and ultimately lose weight. Figures 2, 3, 4, 5 and 6 illustrate the dynamics of food calories consumption, exercise calories exerted, budget calories, budget adherence and weight over time. Users are able to reduce the food calories they consume over time, though we see less noticeable improvements in exercise calories as the increase in exercise appears to not persist across months. The application's effectiveness at getting users to reduce their calories is worth noting, and dieting has been demonstrated to be more effective for weight management than exercise (Karnani, McFerran, and Mukhopadhyay, 2016). Furthermore,

Figure 2: Dynamics of Food Calories Intake over Time

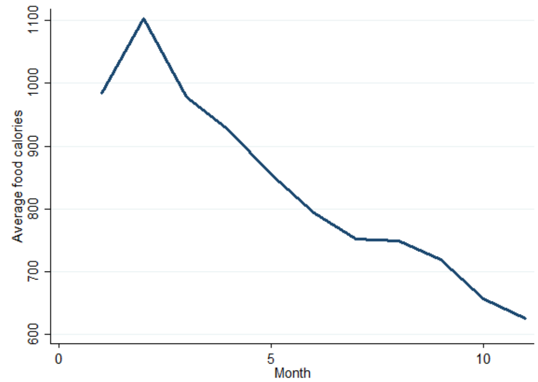


Figure 3: Dynamics of Exercise Calories over Time

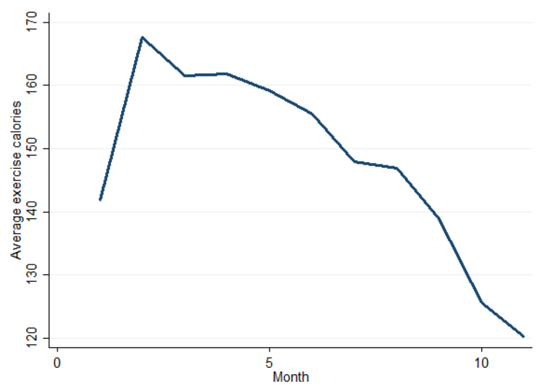


Figure 4: Dynamics of Calories Budget over Time

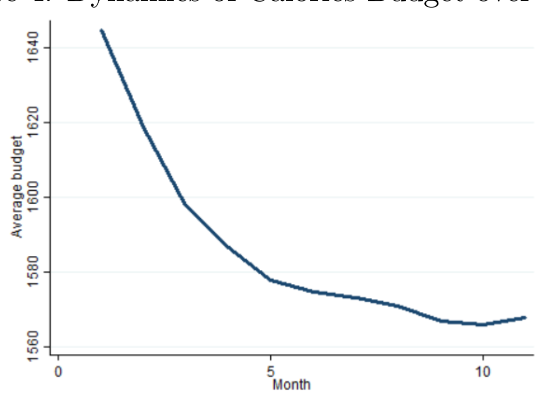


Figure 5: Dynamics of Budget Adherence over Time

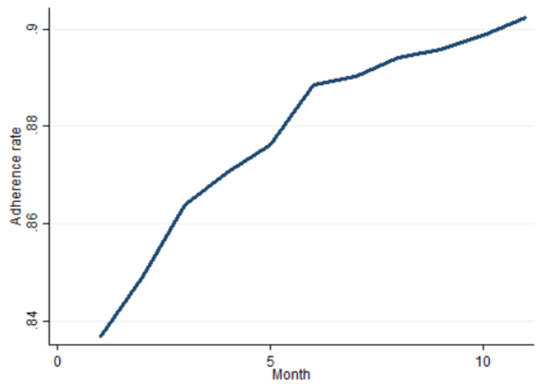


Figure 6: Dynamics of Weight over Time

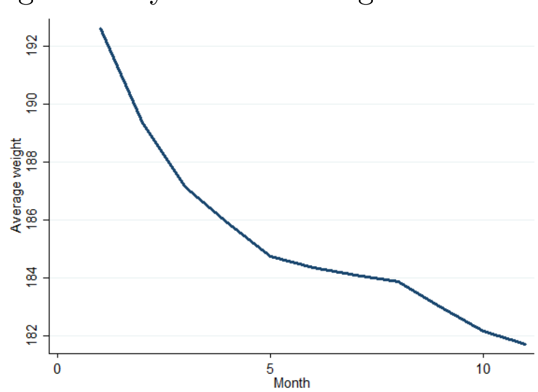
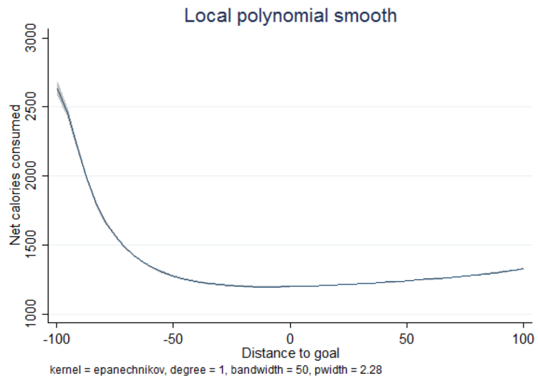


Figure 7: Net Calories Consumed as Approach Weight Loss Goal



the suggested daily limit of calories diminishes over time, as the application will adjust the budget as the user progresses. Even as the budget appears to fall over time, we see that budget adherence is increasing over time. Consequently, the average weight is diminishing over time, which suggests that the application is a helpful tool for managing weight loss.

Finally, we plot the relationship between net calories consumed and distance to weight loss goal in Figure 7. This graph confirms that users consume fewer calories by eating less and/or exercising more as they approach their long-term goal. In other words, the long-term goal serves as an important motivational device for the users.

3.2 Graphical Analysis of the Impact of Short-Term Goals

This section provides the key patterns in our data that lead us to believe the existence of a relationship between short-term and long-term goals. We show the suggestive evidence by illustrating discontinuities caused by being either under or over the calories budget. Before discussing the discontinuities, we first provide some details about short-term goal achievement (or failure). In general, about 14% of the observations pertain to cases in which users exceed the budgeted amount of daily calories; so a large proportion of users are able to stay within the budget, as illustrated in Figure 8. Furthermore, we see both temporal and cross-sectional variation in the extent to which users adhere to the budget. Figure 9 shows

Figure 8: Distribution of Calories Below or Above Daily Budget

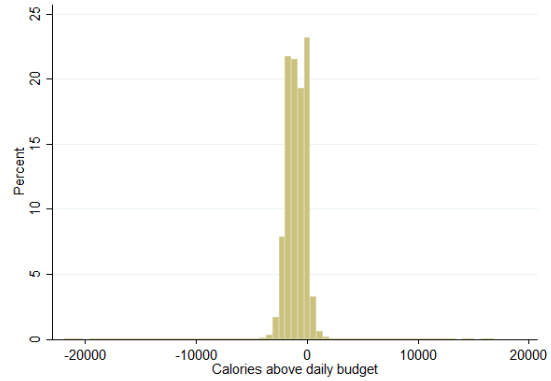
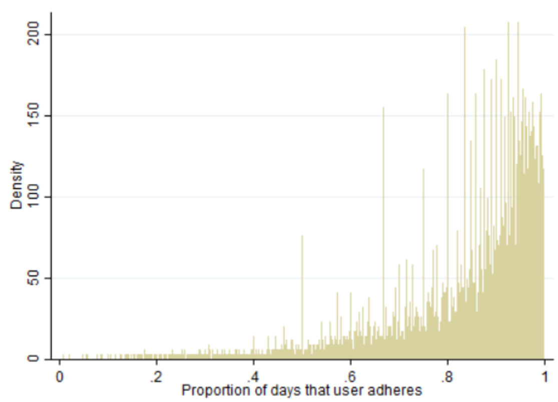


Figure 9: Distribution of Adherence Rates Across Users



a histogram of the percentage of days a user stays within budget. From this image, we see that users are in general able to stay within budget for over 80% of the days; that fact that users do indeed violate the budget highlights also the temporal (i.e., within-user) variation.

To proceed with our graphical analysis, we proceed using the empirical strategy suggested by Imbens and Lemieux (2008). We first construct calories bins with bin-width of 25 calories. For K bins, we can then construct bins $(b_k, b_{k+1}]$ for $k = 1, ..., K$. We then calculate the number of observations n in each bin as

$$N_k = \sum_{n}^{N} 1(b_k < \tilde{c}_n \leq b_{k+1}),$$

where $\tilde{c}_n = c_n - c_n^*$ represents the calories actually consumed net the recommended budget of calories. With this quantity, we can calculate the average outcome in the bin as:

$$\bar{y}_k = \frac{1}{N_k} \sum_{n}^{N} y_n \cdot 1(b_k < \tilde{c}_n \leq b_{k+1}).$$

Figure 10 illustrates the interaction between short-term goal achievement and long-term weight loss progress. The horizontal axis displays the amount of calories below or above the daily budget on a particular day, while the vertical axis represents the next day's weight loss progress (i.e., weight loss). We focus our descriptive analysis on the discontinuity of being either below or above the recommended budget for calories. First notice that around the discontinuity (i.e., point at which the caloric budget is balanced), the difference in weight loss progress for cases where the users are under and over-budget is about 0.025 pounds. In the short-term, there is an improvement in subsequent weight loss progress for those who kept within their calorie budget. Keep in mind that the point to the left of the discontinuity can be interpreted as 25 calories under-budget, while the point to the right of the discontinuity can be interpreted as 25 calories over-budget. Therefore, the horizontal distance between these points that surround the discontinuity is 50 calories. To understand how little food is needed to go from budget adherence to budget violation, we would like to point out that 50 calories is roughly equivalent to one small green apple, one McDonald's Chicken McNugget, or two marshmallows. Furthermore, the magnitude of the discontinuity is nearly double the weight that would be equivalent to 50 calories (i.e., 0.014 pounds). So there appears to be a disproportionately large positive effect of staying within the short-term calories budget, above and beyond the weight loss associated with a 50 calories reduction. We would also like to add that there are 354,666 observations in which the daily calories are within or above the budget by 25 calories.

Furthermore, we see that staying within the calorie budget is associated with a larger benefit in weight loss progress in the intermediate term. Figure 11 shows that weekly weight loss is markedly higher for those who were slightly below the allowed calories as opposed to those who were slightly below the allowed calories. The distance between the weekly weight

Figure 10: Daily Progress in Weight Loss by Amount of Calories Under or Over Budget the Previous Day

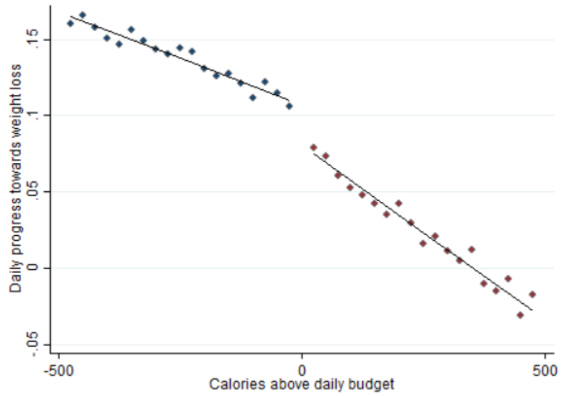
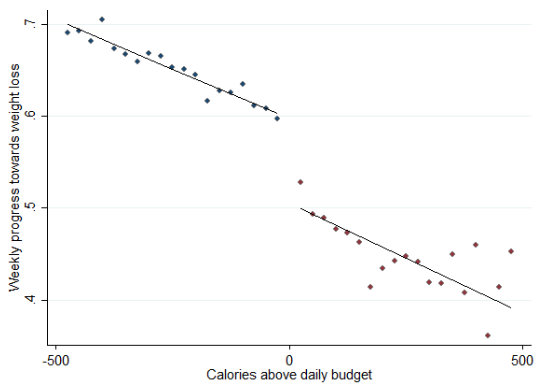


Figure 11: Weekly Progress in Weight Loss by Amount of Calories Under or Over Budget the Previous Day



loss below and above the calorie budget is about 0.1 pounds.

Instead of looking at the weekly weight loss, we can see if there is an even longer-term benefit of short-term goal achievement on monthly weight loss progress. Figure 12 highlights that the monthly weight loss is noticeably larger for those staying within the allowed budget. In this case, monthly weight loss below and above the calorie budget is about 0.5 pounds.

Future budget adherence may be one possible explanation for the observed relationship between short-term goal achievement and long-term weight loss. Figure 13 illustrates that staying within budget today may be associated with a greater likelihood of staying within budget the next day. There are roughly 40,000 more cases where individuals stay within

Figure 12: Monthly Progress in Weight Loss by Amount of Calories Under or Over Budget the Previous Day

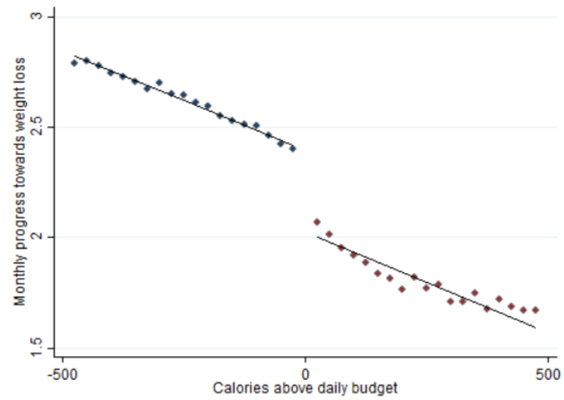
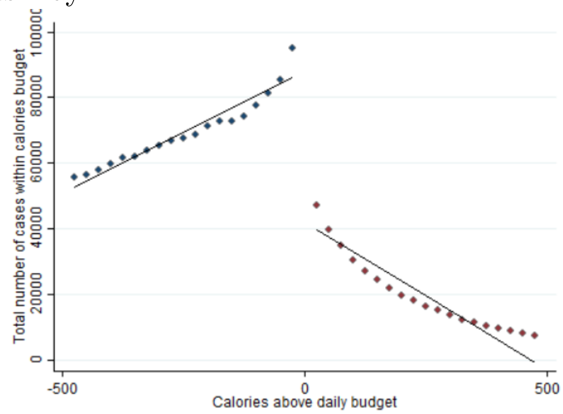


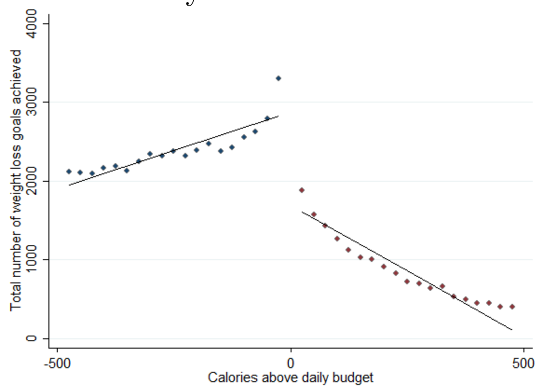
Figure 13: Total Number of Observed Budget Adherence by Amount of Calories Under or Over Budget the Previous Day



budget the next day when they previously stayed within budget as opposed to violating the budget. Staying within the daily budget seems to persist over time, which would consequently lead to great weight loss success in the long-run.

Similar to non-negligible impact that short-term goal achievement have on weekly and monthly weight loss progress, Figure 14 shows that being slightly under-budget in calories can be markedly beneficial in the final stages of the weight loss progress, as the number of instances in which weight loss goals are achieved suffers a discontinuous drop when over-budget. The difference in the number of achieved long-term weight loss goals around the discontinuity is about 100.

Figure 14: Total Number of Instances Weight Loss Goal is Achieved by Amount of Calories Under or Over Budget the Previous Day



Short-term goal achievements also appear to be associated with improvements to the long-term goals themselves. Figure 15 plots the number of instances in which users improve their weight loss goal (i.e., set a goal weight that is even more ambitious than their previous or initial goal) against small deviations of staying within or outside the previous day's daily budget. There is a sharp discontinuity around the budget, and noticeably larger number of cases in which goals are improved when users stay within the budget as opposed to go slightly over the budget. The discontinuity jump is around 40, so the magnitude is non-negligible. Taken together, we interpret short-term goal achievement as having varying impact on long-term goal achievement at different stages of goal progression. In particular, the encouraging effects associated with short-term goal achievement are noticeably larger in the long-run, especially as users are within reach of their ultimate weight loss goal.

Finally, we provide suggestive evidence that short-term goal achievement has implications on customer development via upgrades to premium accounts. Figure 16 shows the relationship between staying within or outside the budget, and the total number of new upgrades - defined as instances in which a user who was previously using a regular account subsequently upgrades to a premium account. The picture shows that the jump around the discontinuity is around 40 additional new upgrades in cases where users stayed within their daily budget as opposed to violating their daily budget. Given that \$3.33 monthly fee for

Figure 15: Total Number of Instances Weight Loss Goal is Improved by Amount of Calories Under or Over Budget the Previous Day

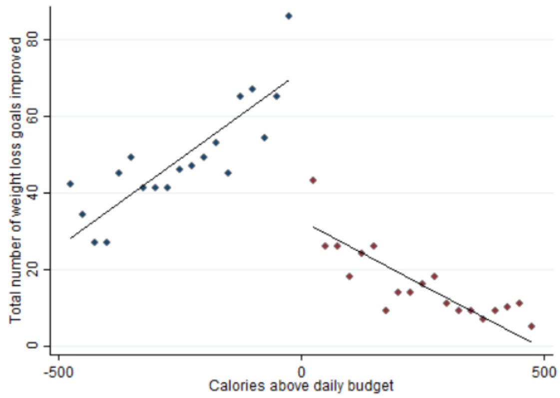
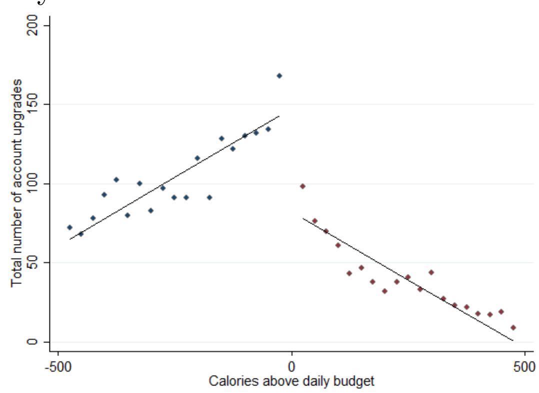


Figure 16: Total Upgrades by Amount of Calories Under or Over Budget the Previous Day



the premium account, this increase in new upgrades would translate into additional revenues of \$1,598 per year, just from the subset of marginal users around the discontinuity.

4 Regression Discontinuity Framework

In this section, we describe a regression discontinuity (RD) design that will be used to analyze the weight loss dynamics. Suppose that an individual i is using a mobile weight loss application at time t, and outcomes that matter to this individual may include future weight loss. The individual receives the outcome of short-term goal achievement, which is indicated by whether or not the individual's calories are within the recommended budget. We let

$a_{it} = 1(c_{it} \leq c^*_{it})$ be an "adherence" indicator for whether or not the individual's actual net calories (c_{it}) is within the calories budget (c^*_{it}); to reflect the weight loss application's daily budgets, we allow c^*_{it} to vary over time and across individual users. Note that we allow the budgeted calories to potentially change over time, say in the event that the user selects a more ambitious (or modest) weight loss target. We can write that some outcome y_i (related to long-term weight loss progress, goal achievement, or more engagement with the mobile application) as

$$y_{it} = \kappa + \theta a_{it-1} + \omega_i + \varepsilon_{it},$$

where ω_i is a user-specific fixed effect, ε_{it} is an i.i.d. shock, and θ is the causal effect of past short-term goal achievement. In general, the short-term achievement is likely correlated with other characteristics that are not observable to the researcher. However, as there are some unpredictable random components to each day's calories intake, a narrowly decided achievement (or violation) of budget likely approximates a randomized experiment. As highlighted in our descriptive analysis, it takes very little food to tip the balance and shift a user from being within-budget to being over-budget. One can then identify the causal effect of short-term goal achievement by comparing cases in which a user barely stayed within budget (i.e., the treatment group) with cases in which the user barely went over-budget (i.e., the control group).

We employ a RD approach that makes use of all the data in our sample. Following Cellini, Ferreira, and Rothstein (2010), we estimate the specification above by using the following:

$$y_{it} = \kappa + \theta a_{it-1} + P(\tilde{c}_{it-1}) + \omega_i + \tilde{\varepsilon}_{it},$$

where $P(\tilde{c}_{it-1})$ is a high-order polynomial function of the running variable (a.k.a., score) $\tilde{c}_{it-1} = c_{it-1} - c^*_{it-1}$. Furthermore, we let $\tilde{\varepsilon}_{it} = \varepsilon_{it} - P(\tilde{c}_{it-1})$. Note that here we normalize the running variable, as there are multiple cutoffs across users and time. In other words, we use the common strategy (Cattaneo, Keele, Titiunik, and Vazquez-Bare, 2016) of pooling all of the observations as though there were only one cutoff at $\tilde{c}_{it-1} = 0$.

5 Main Findings

We first discuss the validity of the regression discontinuity design introduced in the earlier section, followed by a presentation of the reduced-form results.

5.1 Validity of the Regression Discontinuity Design

The main source of concern with respect to the RD design is potential manipulation of the calories entered into the application. If users feel ashamed or guilty about over-indulging in one or more meals, they may have an incentive to manipulate the calories entered, especially so if they are close to the recommended budget. One way they can manipulate the calories entered would be to leave out completely the calories for one or more meals. Omission of meals occurs in a small sub-set of the observations. What we are concerned about is disproportionately more manipulation at the point right below the budget cut-off, as that may be indicative of users attempting to artificially suppress their calories count. We are able to demonstrate that this is indeed not the case. For the observations that are within 25 calories of the budget, the share of them that have omitted meals is 0.3%, while for the observations that are 25 calories above budget, the share of them that have omitted meals is around 0.3% as well. In other words, there doesn't appear to be a strong incentive for users to omit meals as a way to lower their calories count.

We can look more carefully at which meals users did not log calories for and plot the relationship of missing meal entry with the calories above or below budget. In particular, we can verify that there are no sharp discontinuities with respect to missed meals around the cut-off point (see Figures 17, 18, and 19). There does not appear to be a jump in cases where calories from meals are missing to the left of the cut-off.

Figure 17: Likelihood of Missing Breakfast Entry

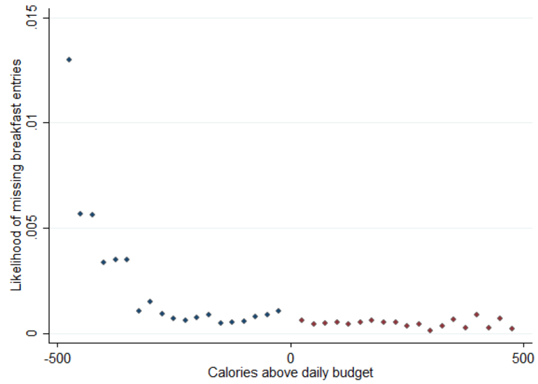


Figure 18: Likelihood of Missing Lunch Entry

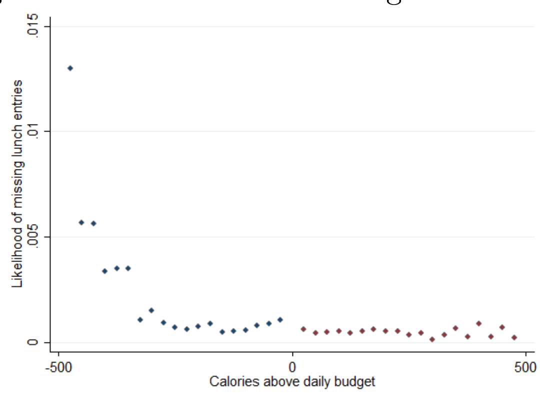


Figure 19: Likelihood of Missing Dinner Entry

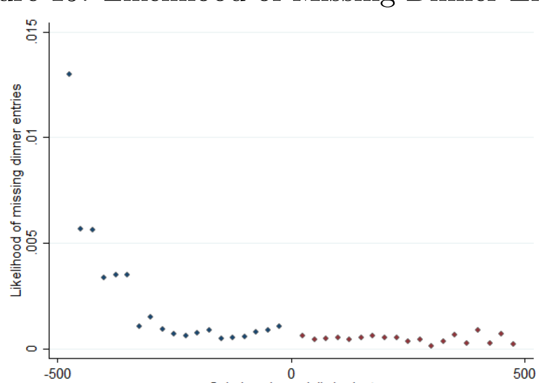


Table 2: Observable Characteristics of those Above and Below the Budget of Calories

	Not adhere		Adhere	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Age	40.33	14.08	39.57	14.09
Male	0.32	0.47	0.33	0.47
Height	66.58	3.83	66.78	3.88
Start weight	189.06	47.74	195.31	50.70
Goal weight	155.97	32.71	159.35	33.95

As suggested by Goldfarb and Tucker (2014), we also show that the users above and below the threshold of daily calories are very similar in terms of observable characteristics. Table 2 shows that the users who do and do not adhere to the daily budget are almost identical in terms of age, gender, and height. There are small differences in terms of start weight and goal weight, though, their weight loss goals are roughly the same (i.e., goal of losing about 35 pounds).

5.2 Baseline Results from Regression Discontinuity Design

We now present our findings from our analysis using regression discontinuity. To implement the RD framework, we make use of local polynomial modeling. As suggested by Lee and Lemieux (2010), we choose a the order of polynomial up until the point in which the higher orders have no economic significance. We also confirm that the parameters associated with the high order polynomial are individually and jointly statistically significant.

All of these results will be consistent with our earlier descriptive analysis with the scatter-plots. Our first set of results in Table 3 confirm that the achievement of short-term goals, in the form of adhering to the daily budget of calories, have positive effects on future weight loss.[19] The estimates show that the short-term goal accomplishment is associated with an increase in future weight loss by 0.12, 0.25, and 0.65 pounds the next day, week, and month

[19] Following the suggestion of Lin, Lucas, and Shmueli (2013), we will avoid coming to conclusions based solely on p-values, as the large data will inevitably lead to large t-statistics.

Table 3: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.124^{***}	0.245^{***}	0.652^{***}
	(0.00239)	(0.00438)	(0.00760)
Constant	0.0156^{***}	0.466^{***}	1.839^{***}
	(0.00186)	(0.00342)	(0.00593)
Observations	7201635	6984165	6150552

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

respectively. One may interpret the constant term as the baseline weight loss, so the lift that short-term accomplishment yields relative to the normal weight loss amount is nearly 1000%. In contrast, the baseline weight loss the next week and next month is quite large, so the impact of adherence is about 50% and 30% respectively. Keep in mind that these weight loss effects are considered to be within the range for what is deemed healthy according to the CDC, as the ideal weight loss per week is recommended not to exceed 2 pounds.

Table 4 shows that when we focus on outcomes related to user engagement with the weight loss application, short-term goal accomplishment can be beneficial as we. First, we provide evidence that adherence of the daily budget today increases the likelihood of adhering to the next daily budget by about 2%. This result is consistent with the notion that short-term goals may help resolve a type of uncertainty users may have. In particular, the empirical relationship between current and future short-term goal achievement may reflect user learning about the degree of will-power they have (e.g., Bénabou and Tirole, 2004) as staying within the budget of calories require a large degree of self-control. Furthermore, we see that users are more likely to upgrade. Note that the impact that adherence on upgrade probability appears small, however, keep in mind that the baseline upgrade probability is quite small to begin with. So compared with the constant term, the increase in upgrade propensity is

Table 4: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0241***	0.000216***
	(0.000507)	(0.0000487)
Constant	0.751***	0.00113***
	(0.000396)	(0.0000380)
Observations	7201635	7201635

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

roughly 20% of the baseline upgrade propensity. Users who end up upgrading are never observed to downgrade back to the free version in our sample, so the stream of revenues from monthly fees can potentially be quite large.

5.3 Results Across Segments and Contexts

We next investigate the extent to which the positive long-term effect of short-term goal achievement differs across various user segments. The main segments that the firm can easily identify in this weight loss application are based on gender and age. Understanding whether such differences exist can help the mobile application design gender-specific goals so as to maximize long-term performance. Note that gender, age and initial BMI are particularly relevant segments in the weight loss context, and studies about weight management tend to focus on these characteristics (e.g., Flegal, Carroll, Kuczmarski, and Johnson, 1998; Koritzky, Techiam, Bukay, and Milman, 2012). From a practical perspective, these user characteristics are available upon registration, so it would be possible to modify the suggested daily calories budget according to the user segment. In addition to these user characteristics, one may also segment them based on their past performance, such as whether or not they struggled with weight loss as of late. Finally, users may act differently depending on the situational

Table 5: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss Across Genders

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.0982***	0.223***	0.572***
	(0.00266)	(0.00489)	(0.00847)
Adhere x Male	0.0892***	0.0751***	0.275***
	(0.00400)	(0.00736)	(0.0128)
Constant	0.0137***	0.464***	1.833***
	(0.00186)	(0.00342)	(0.00593)
Observations	7201635	6984165	6150552

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

context, such as around New Year's when there is added focus towards weight loss because of New Year's resolutions.

To estimate gender-specific effects, we include an interaction term in our specification. These results can be found in Tables 5 and 6. A few observations are in order. First, we see that the positive effect of short-term achievement on future weight loss is magnified for male users. However, male users also appear to be complacent the next day if they were within their daily budget, as they are more likely to violate their daily budget a day after being within their budget. Finally, from the perspective of the weight loss application, there is nearly a 1% lift in premium upgrades from short-term goal achievement among the male users.

Next we study differences in the short-term goal achievement effects across different age groups. To proceed, we place users into three age groups; namely, those who are less than 30 years old (i.e., baseline group), those who are between 30 to 60, and those who are older the 60. Using this age group categorization, we then repeat our analysis above by interacting the short-term goal achievement with the various age groups. These results are shown in Tables

Table 6: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application Across Genders

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0396***	0.0000296
	(0.000565)	(0.0000543)
Adhere x Male	-0.0530***	0.000637***
	(0.000851)	(0.0000818)
Constant	0.752***	0.00112***
	(0.000396)	(0.0000380)
Observations	7201635	7201635

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

7 and 8. In terms of future weight loss, short-term goal achievement seems to benefit the older users more than the younger ones. In contrast, younger users appear to use short-term goal achievements to propel them to stay within budget in subsequent days, more so than their older counterparts. Finally, the younger age group seems most receptive to upgrade their account to premium in light of short-term goal achievements.

Our next set of analysis looks at how the impact of short-term achievement may differ across users based on their starting BMI levels. Tables 9 and 10 provides the results from our analysis. In these specifications, we consider interactions between the short-term goal achievement with a indicator for whether the user has an above-average BMI (relative to other users of the mobile application). The short-term goal achievement seems to be disproportionately beneficial to those who began at a higher BMI level. However, those with high BMI seem less likely to create momentum in accomplishing subsequent short-term goals. Furthermore, those with lower BMI to begin with are more likely to upgrade their account in light of short-term goal achievements.

Users may also differ depending on how well they are progressing with weight loss. Given

Table 7: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss Across Age Groups

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.0964***	0.245***	0.698***
	(0.00403)	(0.00741)	(0.0188)
Adhere x 30-60 Years	0.0342***	-0.00240	-0.0363
	(0.00437)	(0.00804)	(0.0199)
Adhere x 60 Years or Older	0.0505***	0.00928	0
	(0.00683)	(0.0126)	(.)
Constant	0.0166***	0.466***	1.841***
	(0.00186)	(0.00343)	(0.00594)
Observations	7201635	6984165	6150552

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 8: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application Across Age Groups

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0341***	0.000372***
	(0.000857)	(0.0000824)
Adhere x 30-60 Years	-0.0111***	-0.000266**
	(0.000929)	(0.0000893)
Adhere x 60 Years or Older	-0.0241***	0.000120
	(0.00145)	(0.000140)
Constant	0.750***	0.00113***
	(0.000396)	(0.0000381)
Observations	7201635	7201635

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 9: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss Across BMI Levels

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.110***	0.223***	0.578***
	(0.00279)	(0.00513)	(0.00888)
Adhere x High BMI	0.0388***	0.0560***	0.198***
	(0.00383)	(0.00705)	(0.0122)
Constant	0.0139***	0.463***	1.830***
	(0.00187)	(0.00343)	(0.00595)
Observations	7201635	6984165	6150552

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 10: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application Across BMI Levels

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0364***	0.000259***
	(0.000594)	(0.0000571)
Adhere x High BMI	-0.0324***	-0.000113
	(0.000814)	(0.0000782)
Constant	0.752***	0.00113***
	(0.000397)	(0.0000382)
Observations	7201635	7201635

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 11: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss Across Users With Varying Levels of Struggle

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.106***	0.239***	0.570***
	(0.00251)	(0.00462)	(0.00801)
Adhere x Gained weight	0.140***	0.0422***	0.404***
	(0.00497)	(0.00911)	(0.0156)
Constant	0.0455***	0.475***	1.836***
	(0.00198)	(0.00365)	(0.00633)
Observations	7201635	6984165	6150552

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

the challenging nature of weight loss, users are bound to gain weight every now and then. What may make this application particularly effective is its ability to motivate those who are currently struggling. For this reason, the segment of users who have struggled in the past is particularly important. So in our next specifications, we investigate whether or not short-term goal accomplishment is particularly effective with this potentially vulnerable segment of users. Tables 11 and 12 show that short-term goal achievement has a disproportionately larger positive effect for those who gained weight the previous day. This positive effect materializes in both long-term weight loss as well as engagement with the application. Most importantly, we note that the likelihood a user continues to stay within budget the next day is particularly pronounced if that user gained weight in the past. Therefore, we interpret short-term goals as an effective motivational tool to keep who have struggled on track towards their weight loss goals.

As this application asks users for their goal weights, we can identify another segment

Table 12: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application Across Users With Varying Levels of Struggle

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0227***	0.000178***
	(0.000534)	(0.0000513)
Adhere x Gained weight	0.0121***	0.000130
	(0.00106)	(0.000102)
Constant	0.754***	0.00109***
	(0.000422)	(0.0000405)
Observations	7201635	7201635

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

based on the ambitiousness of their goals. A common pitfall of dieting is the use of overly ambitious weight loss targets. We now explore the extent to which short-term goals can be used to off-set overly ambitious long-term goals. For this analysis, we consider interactions between the short-term achievement effect with an indicator for whether or not the user's target weight is overly ambitious. As overweight people in general aim to lose 30% of their body mass,[20] we will label those who aim to lose more than this amount as having set an ambitious goal. Tables 13 and 14 show our findings from these specifications. First, we note that short-term achievements have an especially large positive effect on future weight loss for those with ambitious goals. However, we do not see similar patterns when the outcomes involve engagement with the application. In fact, the interaction term is negative when the outcome is adherence to future daily budgets.

A situational factor that may affect user behavior is New Year's. This is a time when people often make New Year's Resolutions, and losing weight is arguably the most common resolution (e.g., Kassirer and Angell, 1998). Given the added focus on weight loss around this

[20] See, for example, "Is Your Weight Loss Goal Realistic?" (*WebMD*, 2005)

Table 13: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss Across Users With Varying Levels of Ambition

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.120***	0.238***	0.627***
	(0.00245)	(0.00451)	(0.00781)
Adhere x Ambitious	0.0459***	0.0694***	0.269***
	(0.00590)	(0.0109)	(0.0191)
Constant	0.0148***	0.465***	1.834***
	(0.00186)	(0.00343)	(0.00594)
Observations	7201635	6984165	6150552

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 14: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application Across Users With Varying Levels of Ambition

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0247***	0.000225***
	(0.000522)	(0.0000501)
Adhere x Ambitious	-0.00663***	-0.0000889
	(0.00126)	(0.000121)
Constant	0.751***	0.00113***
	(0.000396)	(0.0000381)
Observations	7201635	7201635

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 15: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss Around New Year's

	(1) Next day	(2) Next week	(3) Next month
Adhere	0.122***	0.219***	0.517***
	(0.00239)	(0.00439)	(0.00757)
Adhere x New Year	0.0660***	0.604***	2.954***
	(0.00357)	(0.00650)	(0.0107)
Constant	0.0155***	0.465***	1.837***
	(0.00186)	(0.00342)	(0.00589)
Observations	7201635	6984165	6150552

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

time of year, we explore how and if the short-term goal achievements complement such temporal motivations. In these next specifications, we consider interactions between short-term goal accomplishment and an indicator for the month of January. Tables 15 and 16 provide the estimates from these specifications. We first note that short-term goal achievement has a stronger positive effect around New Year's on future weight loss in subsequent days, weeks, and months. There is also a stronger positive relationship around New Year's on upgrade propensity. Where we see a negative interaction is with respect to adherence to the next daily budget. That is, users appear to be more complacent around New Year's soon after achieving their daily goals.

Another situational factor may be the day of week. This factor may be relevant if users become depleted or energized by the end of the week. For this next specification, we investigate interactions between the adherence effect with the day of week. Figure 20 displays the impact of short-term goal achievement (on future daily weight loss) across different days of the week. We see that the adherence effect is strongest on Sunday, but then diminishes towards Wednesday, and then increases again until Friday. One may interpret this result as

Table 16: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application Around New Year's

	(1) Adhering to next daily budget	(2) New upgrade
Adhere	0.0246***	0.000108*
	(0.000508)	(0.0000488)
Adhere x New Year	-0.0131***	0.00257***
	(0.000759)	(0.0000729)
Constant	0.751***	0.00113***
	(0.000396)	(0.0000380)
Observations	7201635	7201635

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

demonstrating potential within-week dampening effects of short-term goal achievement.

5.4 Dynamic Effects of Short-Term Goal Achievement

In this section we explore more closely the long-term impact of short-term goal achievement. To proceed, we adopt an alternative specification that allows for lagged short-term goal achievements. Following closely the dynamic RD design laid out by Cellini, Ferreira, and Rothstein (2010),[21] we use the following dynamic RD design:

$$y_{it} = \kappa + \sum_{\tau}^{\infty} [\theta_\tau a_{it-\tau} + P(\tilde{c}_{it-\tau})] + \omega_i + \tilde{\varepsilon}_{it}.$$

With this specification, we can investigate how θ_τ evolves as the past short-term goal accomplishment becomes more distant to the current day. As before, we define $P(\tilde{c}_{it-\tau})$ to be a high-order polynomial.

[21] Another recent application of dynamic regression discontinuity design is Gilraine (2016).

Figure 20: Adherence Effect Across Days of Week

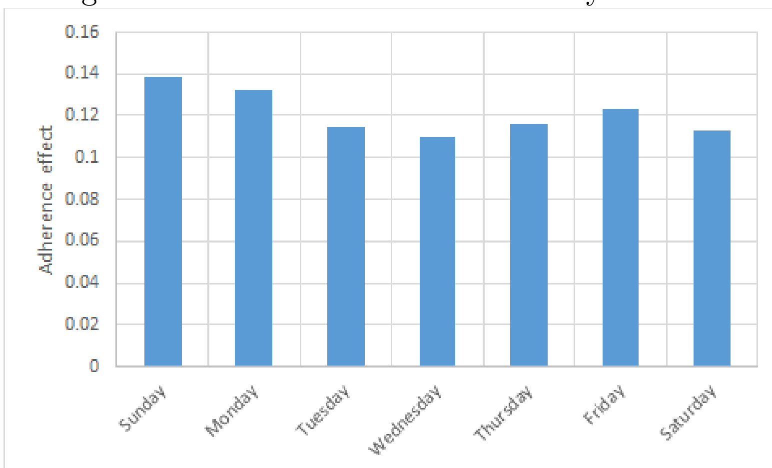


Figure 21: Impact of Short-Term Goal Accomplishment on Daily Weight Loss Over Time

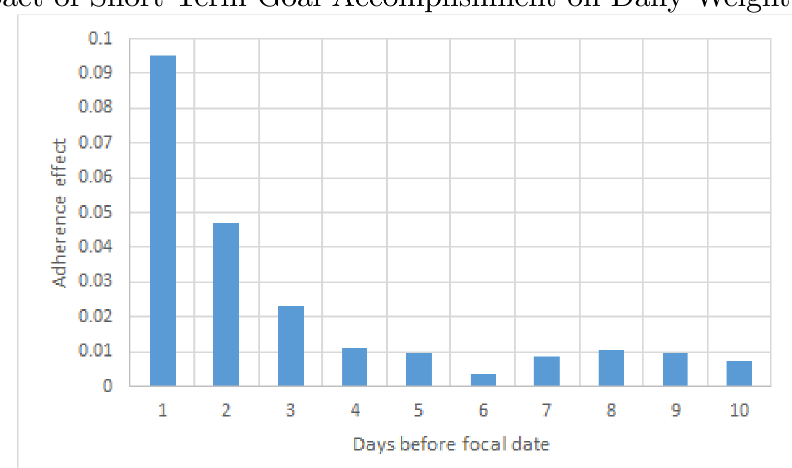
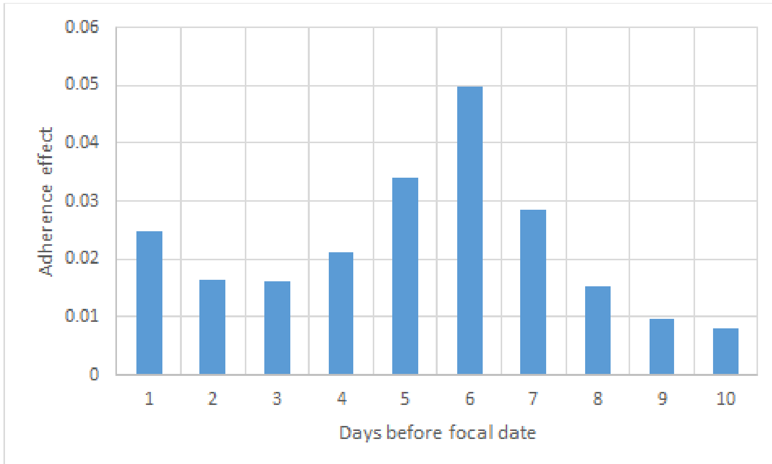


Figure 21 summarizes the impact of short-term goal achievement on daily weight loss as the time of achievement gets further from the current time period. Note that as the estimates all have p-values close to 0, we only report the point estimates. This picture highlights that short-term goal achievements can have an impact in the days following the achievement, though, at a diminishing rate. By the 10th day following the date of achievement, the effect is noticeably smaller than its impact the day immediately following a short-term achievement. These results further highlight the role that short-term achievements have on future short-term achievements, as some of the gains in long-term weight loss may be attributed to such momentum effects, as opposed to being directly impacted by the earlier achievement itself. Furthermore, the adherence effect seems to converge towards 0.01, which establishes a fairly persistent (albeit small in magnitude) effect even after several days.

Next we investigate the temporal effect of short-term goal achievement on future short-term goal achievement. Figure 22 provides the main results from this analysis. It is interesting to note that the positive effect from short-term accomplishments evolves non-monotonically over time. That is, staying within budget has the effect of increasing future budget adherence by about 2.5%, which then decreases a couple days from the focal date, but later jumps up towards 5% nearly a week before the focal date. Though by the 10th day, the effect falls down to about 1%. Combined with the earlier graph, this table suggests that not only is there a direct impact from short-term goal achievement over time, there may also be an indirect impact from future budget adherence. Furthermore, the persistent nature of these effects would suggest that these short-term motivational gains accumulate over time, which ultimately helps facilitate long-term weight loss towards the goal.

In fact, we are able to show that short-term goal accomplishments propel users to accomplish future short-term goals that are more challenging. As the mobile application makes periodic updates to the daily budget, users may face increasingly challenging daily goals over time as they progress. Figure 23 illustrates that accomplishing a short-term accomplishment has an immediate effect on the next day's likelihood of accomplishing a more challenging

Figure 22: Impact of Short-Term Goal Accomplishment on Future Budget Adherence Over Time



goal by about 3%. This positive effect also appears to be persistent over time, though it diminishes significantly 10 days afterwards.

We repeat this analysis using premium upgrades as the outcome of interest, and different dynamics emerge. Figure 24 displays the estimates for the short-term achievement effect on subsequent upgrade decisions. Upgrades appear to be most pronounced the day after the short-term goal achievement, and quickly fall in the subsequent days. However, the effect re-emerges several days after, which may suggest that users may dwell on the short-term achievements before committing to the premium services offered by the application.

Our findings that past short-term successes (even after several days) have an impact on current weight loss progress is consistent with recent research in psychology, which has demonstrated that successful dieters are those who process time-distant information in their decision making as opposed to using only very recent information (Koritzky, Rice, Dieterle, and Bechara, 2015). This result, along with the past insights from psychology, would suggest that users may benefit from being able to access their historical progress in weight loss.

Figure 23: Impact of Short-Term Goal Accomplishment on Future Adherence of More Challenging Budgets Over Time

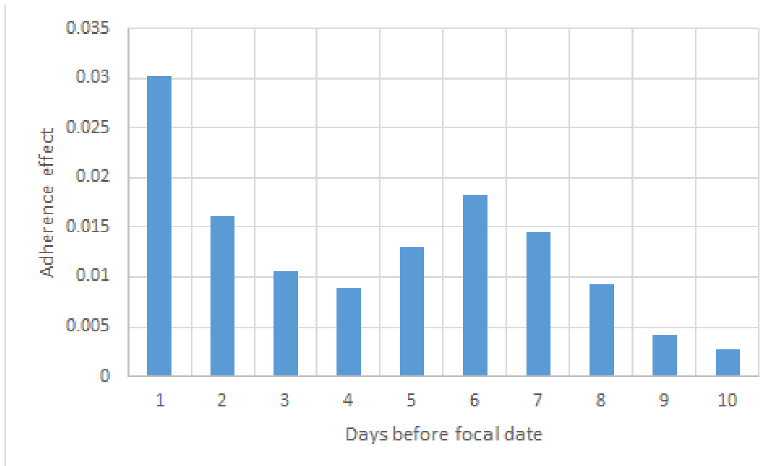
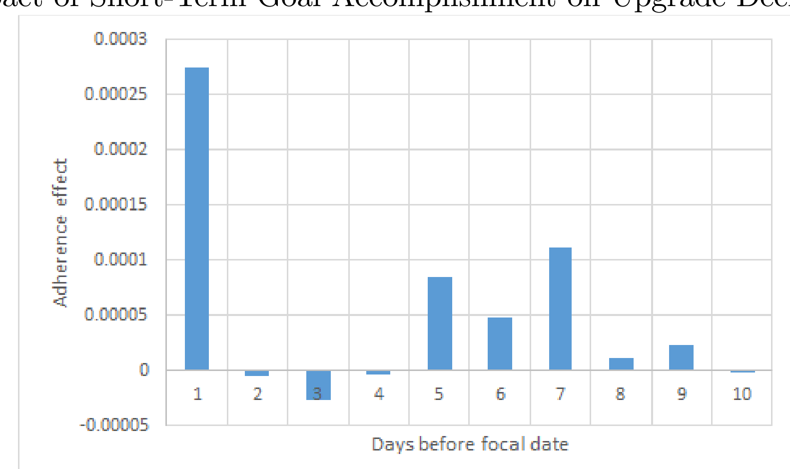


Figure 24: Impact of Short-Term Goal Accomplishment on Upgrade Decisions Over Time



5.5 Short-Term Achievement and Distance to Long-Term Goal

In this section we provide a discussion about the impact of staying within the daily budget as the user gets closer to the long-term weight loss goal. The user's motivation may differ as the long-term weight loss target is more or less attainable. To study the potential relationship between short-term goal achievement and distance to ideal weight, we consider the following extension of our baseline specification,

$$y_{it} = \kappa + \theta a_{it-1} + \gamma_1 a_{it-1} \times D_{it-1} + \gamma_2 a_{it-1} \times D_{it-1}^2 + \gamma_3 a_{it-1} \times D_{it-1}^3 + P(\tilde{c}_{it-1}) + \omega_i + \tilde{\varepsilon}_{it},$$

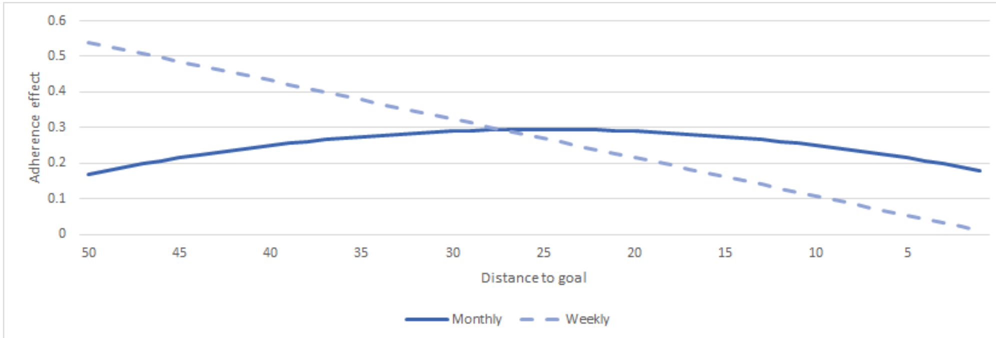
where D_{it-1} is a measure of how much more weight user needs to lose in order to reach the target long-term weight. We allow for potential non-monotonicities as well by including the cubed and cubic versions of this interaction.

Figure 25 plots the part of the adherence effect that varies with distance to goal. A few patterns emerge. First, the weekly weight loss progress appears to be most pronounced as the user is far away from the long-term weight loss goal. In other words, short-term goal achievement is an especially helpful motivator when the user has much weight to lose before reaching the ultimate goal. This insight is particularly valuable as users who are far away from their goal may feel negative emotions and stress, which would ultimately derail their weight loss efforts (e.g., Elfhag and Rössner, 2005). Second, the effect of short-term goal achievement on monthly weight loss progress appears to be non-monotonic with respect to distance to goal, as it initially increases as the user approaches the goal, plateaus at a distance of 25 pounds, and then decreases as the weight target becomes much closer.

5.6 Robustness Checks

The RD design relies on notion that the users do not have precise control over the running variable (i.e., how much under or over-budget they are with respect to calories). In the

Figure 25: Short-Term Goal Achievement Effect as User Approaches Ideal Weight



next set of robustness checks, we investigate whether our results hold in cases in which users plausibly have even *less precise control* over calories. We will run this robustness check using a multi-step process. In the first step, we formulate a linear model to predict the running variable $\tilde{c}_{it}$ using observations of lagged values of this variable,

$$\tilde{c}_{it} = \sum_{l}^{L} \delta_l \tilde{c}_{it-l} + \eta_i + \xi_{it},$$

where L is the number of lags, η_i is a user fixed-effect, and ξ_{it} is an i.i.d. shock. This specification is reasonable as healthy behavior tends to exhibit momentum and persistence (e.g., Acland and Levy, 2013; Charness and Gneezy, 2009; Uetake and Yang, 2016). Table 17 provides the estimates from this specification. As expected, we see that deviations from the suggested calories are affected by past deviations.

With the estimated model above, we can then obtain a prediction interval for the running variable as follows:

$$PI = [\hat{c}_{it} - 1.96 \times se(\xi_{it}), \hat{c}_{it} + 1.96 \times se(\xi_{it})].$$

We will then focus on cases in which $\tilde{c}_{it}$ exceeds the upper bound of the prediction interval; that is, cases in which the user consumes a greater amount of net calories than their historical

Table 17: Linear Model for Running Variable

	(1)
	$\tilde{c}_{it}$
$\tilde{c}_{it-1}$	0.392***
	(0.000376)
$\tilde{c}_{it-2}$	0.159***
	(0.000403)
$\tilde{c}_{it-3}$	0.0770***
	(0.000406)
$\tilde{c}_{it-4}$	0.0652***
	(0.000403)
$\tilde{c}_{it-5}$	0.0960***
	(0.000375)
Constant	-192.0***
	(0.374)
Observations	7056655
R^2	0.43

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 18: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Weight Loss with Weight Loss Application For Sub-Sample of Cases where User Has Less Control

	(1)	(2)	(3)
	Next day	Next week	Next month
Adhere	0.229***	0.0855**	0.235***
	(0.0258)	(0.0274)	(0.0434)
Constant	-0.0369	0.336***	1.671***
	(0.0196)	(0.0208)	(0.0329)
Observations	261509	256588	231938

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

evolution of calories would predict. This robustness analysis avoids cases in which $\tilde{c}_{it}$ lies below the lower bound of the prediction interval, as these may be induced by manipulation on the part of users. The sub-set of cases we are considering in this robustness check can be thought of cases in which a user consumed more calories than anticipated at the time of eating.

Tables 18 and 19 confirm that for the most part, our findings still hold even for this sub-sample of observations in which the users likely have less precision. That is, short-term goal achievement continues to have a positive effect on future weight loss for the sub-sample of cases with higher-than-predicted values for the running variable. However, we see that the short-term goal accomplishment is no longer positively related with upgrades to premium. One possible explanation for this negative effect is that consuming a greater amount of calories compared with the personal norm may reflect poorly on the application, and thus, dissuade users from upgrading. Substantively, this negative result suggests potential boundary conditions for the short-term goal achievement effect, in that staying within budget alone

Table 19: Regression Discontinuity Specification for the Relationship Between Short-Term Goal Achievement and Long-Term Engagement with Weight Loss Application For Sub-Sample of Cases where User Has Less Control

	(1)	(2)
	Adhering to next daily budget	New upgrade
Adhere	0.0103**	-0.00178**
	(0.00367)	(0.000575)
Constant	0.669***	0.00290***
	(0.00278)	(0.000436)
Observations	261509	261509

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

may not be enough to persuade users to upgrade if their performance today deviates from their past performance.

6 Structural Model Analysis

To investigate further the encouraging effect of short-term goal achievement and estimate a dynamic model of calories consumption. We proceed by first presenting a simple model that, followed by a brief discussion about estimation, and then a summary of main findings from structural estimation.

6.1 Dynamic Model of Calories Management

In this section, we describe the model used for structural estimation. Consider a setting in which there are $i = 1, ..., I$ individuals who use the mobile weight loss application. At the beginning of each time period $t = 1, ..., T$, they decide upon how many food calories to consume, f_{it}, and how many exercise calories to expend e_{it}. Their net calories is then calculated to be $c_{it} = f_{it} - e_{it}$. At the beginning of each time period, they are given a recommended budget c_{it}^* of calories they should stay within. Therefore, they are within the budget if $c_{it} - c_{it}^* \leq 0$, which we use a dummy $a_{it} \in \{0, 1\}$ to indicate whether or not the user adhered to the budget. Furthermore, we define $g_{it-1} = (w_{it-1} - w_{it})/(w_{i0} - w_{it-1}^*)$ to measure the progress user i made towards reaching the desired target w_{it-1}^*, where, w_{it} is the individual's current weight. Note that we normalize the progress towards the long-term goal by $w_{i0} - w_{it-1}^*$, as heavier users that start out at higher weights (i.e., large w_{i0}), may be able to lose larger weight increments.

We specify weight to evolve according to the following process:

$$w_{it} = \delta_w w_{it-1} + \delta_f f_{it} + \delta_e e_{it} + \eta_{it}. \tag{1}$$

Based on this specification, we model weight as evolving in an auto-regressive manner. Furthermore, current weight is affected by the current level of calories intake. Furthermore, their one-shot utility for a given level of food and exercise calories is

$$U(X_{it}) = \theta_f f_{it} + \theta_e e_{it} + \theta_a a_{it-1} + \theta_g g_{it-1} + \omega_i + \xi_{it} + \varepsilon_{it}, \tag{2}$$

where θ_a represents their boost in confidence from achieving their short-term goal in the last time period $t-1$, θ_f captures utility users get from consumption of food calories, θ_e is the contribution of exercise calories on utility, θ_g is the utility they get from making progress towards their weight loss target, ω_i captures individual-specific heterogeneity, ε_{it} is an i.i.d. shock that may represent idiosyncratic tastes towards food consumption and exercise (that is known to the user). Note that we also include ξ_{it}, which is an i.i.d. optimization error (that is unknown to the user). One way to interpret this optimization error is that users may not have a complete sense of the actual calories they have consumed during the data; for example, they may enter the food they ate at the end of the day, at which point they may have over-estimated or under-estimated the amount of calories for each food item they ate. Therefore, ξ_{it} may cause users to *inadvertently* go above or below their suggested budget of calories. An important assumption we make for this baseline specification is that ξ_{it} and ε_{it} are not correlated with one another. If we maintain our interpretation of ξ_{it} as an optimization error, this assumption seems reasonable as that users are likely unaware of such errors *ex ante*, otherwise they would not ignore such information. We define the user's state space as:

$$X_{it} = \{f_{it-1}, e_{it-1}, w_{it-1}, \omega_i, \varepsilon_{it}\}. \tag{3}$$

The individuals are forward looking, so they maximize their discounted utility $\sum_s \beta^s U_{it+s}$, with $U_{it+s} = U(X_{it+s})$. It is natural to think about users as being forward looking, as the consumption of calories has implications on their current and future weight, and ultimately, implications on how much progress they make towards their long-run goal. For this reason, it is important to take into account their expectations about future short-term and long-term goal achievements conditional on their current state. Given that the individuals are forward looking, we assume that the users solve an infinite horizon dynamic programming problem, and follow a stationary Markov Perfect Equilibrium. Thus, their optimal consumption of calories σ^* satisfies the following condition

$$V(X_{it}; \sigma^*) \geq V(X_{it}; \sigma), \tag{4}$$

where $V(\cdot)$ is the Bellman equation defined as

$$V(X_{it}; \sigma) = \max_{f_{it}, e_{it}} \{E[U(X_{it}) + \beta E(V(X_{it+1}; \sigma))]\}. \tag{5}$$

6.2 Estimation and Identification Strategy

To estimate this model, we adopt the two-step procedure in Bajari, Benkard, and Levin (2007). This procedure is ideal as it allows us to maintain continuity of the action and state space. Preserving continuity is particularly important in our setting, as we rely on local variation in net consumed calories around the recommended, and making the state space discrete would effectively eliminate much of this variation. Furthermore, the discretization of the state space may introduce new issues regarding user heterogeneity (above and beyond the usual fixed effects), as each user has a different start (and goal) weight, and therefore each user may need to have a different grid of states scaled according to their initial conditions. We now describe each of the steps in our estimation procedure.

6.2.1 Policy Function Approximation

In this step, we use flexible linear regressions to approximate the policy functions for f_{it} and e_{it}. The regressors would then be the pay-off relevant states, their polynomials, as well as interactions between states. In particular, we can write out these regressions as follows:

$$f_{it} = \psi_1 + \psi_1 X_{it} + \psi_2 \breve{X}_{it} + \nu_{it}^f, \tag{6}$$

$$e_{it} = \psi_1 + \psi_1 X_{it} + \psi_2 \breve{X}_{it} + \nu_{it}^e, \tag{7}$$

where $\breve{X}_{it}$ is a flexible function of the pay-off relevant states X_{it}, and ν_{it}^f and ν_{it}^e are i.i.d. shocks. One may interpret ν_{it}^f and ν_{it}^e as approximating the (unobserved) variation in the composite error term $\xi_{it} + \varepsilon_{it}$. The presence of an optimization error (ξ_{it}) that leads users to *deviate* from the amount of calories they planned to consume given the current state. These shocks are neither observed by the researcher, nor are they known *ex ante* to users when they form their decisions. For example, ν_{it}^f may represent calories the user *did not plan* on consuming, but ended up consuming. Analogously, ν_{it}^e can represent a situation in which the user exercised more or less than planned, say if user took flight of stairs instead of elevator because of an outage. The presence of an idiosyncratic shock (ε_{it}) may lead users to deviate from the expected food and exercise calories because of short-term tastes, situations, or needs.

6.2.2 Forward Simulations

Using the policy function approximations, as well as the initial states, we then conduct forward simulations to obtain the approximated value functions. In particular, for any given initial state X_{i1}, we can forward simulate the following:

$$\bar{V}_i(X_1; \sigma, \theta) \simeq \frac{1}{\bar{S}} \sum_{s=1}^{\bar{S}} \sum_{\tau=1}^{T} \beta^{\tau-1} U_i(\sigma(X_\tau^s), X_\tau^s, ; \theta),$$

where each s represents each simulation of length T. We generate two types of approximated value functions at this stage, namely value functions in equilibrium as well as value functions off-equilibrium. The equilibrium value functions are generated using the approximated policy functions (which are assumed to be equilibrium decisions), while the off-equilibrium value functions are generated using perturbations of the policy functions. These approximated value functions can then be compared with one another, and we would use them in minimum distance estimation. The minimum distance estimator searches for structural parameters that minimize violations of the equilibrium requirement (i.e., cases in which the off-equilibrium values exceed equilibrium values). More specifically, with this construction of forward simulated actions and utility, we can then consider perturbations of the policy function to generate K alternative policies. With each alternative policy, we can obtain the forward simulated utility stream using the previous step. We let k index the individual inequalities, with each inequality consisting of an initial state X_1^k and an alternative policy $\tilde{\sigma}$. The difference in valuations for using inequality k is denoted by

$$g_{i,k}(\hat{\sigma}, \theta) = \bar{V}_i(X_1^k; \hat{\sigma}, \theta) - \bar{V}_i(X_1^k; \tilde{\sigma}, \theta).$$

This difference should be positive in equilibrium, since off-equilibrium values have to be lower than discounted profits under equilibrium. Therefore, this criterion listed below identifies a

$\hat{\theta}$ to minimize the violations of the equilibrium requirement:

$$Q(\theta) = \frac{1}{K}\sum_{i}\sum_{k=1}^{K}(\min\{g_{i,k}(\hat{\sigma},\theta),0\})^2.$$

6.2.3 Identification

To identify the model, we rely on rich cross-sectional and temporal variation in food calories, exercise calories, and weight. A long panel allows us to identify the auto-regressive evolution of weight, w_{it}. Furthermore, we can separately identify the utility function and auto-regressive process for weight as a_{it-1} and g_{it-1} do not directly enter the process for w_{it}, while in contrast, these terms enter the utility function directly. Finally, local variation in net calories consumed around the budget of calories c^*_{it} helps us identify the impact of short-term goal achievement on utility, whereby this variation is highlighted extensively in the previous sections of our paper.

6.3 Results from Structural Estimation

We describe the main findings from structural estimation in this section. For the second-stage estimation, we generate 100 random inequalities, in which each inequality compares the forward-simulated value functions in equilibrium with alternative decisions that are generated via perturbations of the approximated policy function from the first-stage estimation procedure. Furthermore, we calibrate the discount factor to be $\beta = 0.99$.[22] Note that we set a high discount factor as t represents a day, so the amount users discount future days may be quite little (unlike other dynamic structural models that measure time as months or years).

Table 20 summarizes the key parameters from the auto-regressive weight process as well as the underlying utility function. Our weight regressions reveal that the biggest determinant of future weight is past weight. As expected, consumption of food calories contributes positively

[22] Gordon and Sun (2015) also set a high value for the discount factor in their dynamic model.

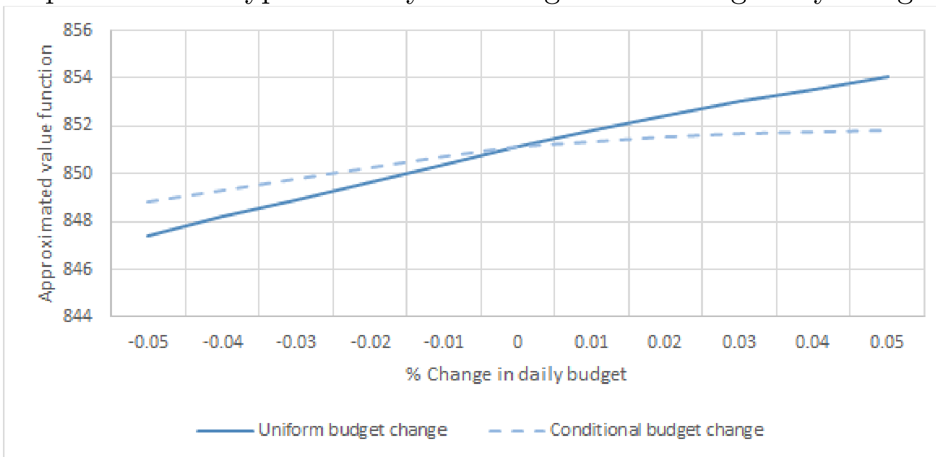
Table 20: Structural Parameter Estimates

	Estimates	**Std. Error**
Weight process		
δ_w	0.997950	0.0000
δ_f	0.000362	0.0000
δ_e	0.000198	0.0000
Utility		
θ_f	0.005995	0.0000
θ_e	0.001663	0.0000
θ_a	0.505470	0.0000
θ_g	0.831606	0.0000

to weight. Exercise calories appear also to be positively related to weight, though exercise need not necessarily lead to weight loss as muscle mass gained from exercising is denser and heavier than body fat.

The utility function points to some interesting aspects about weight loss efforts. Users receive positive (albeit small) utility from consumption of food calories (θ_f), while they receive an even smaller utility from exercising calories (θ_e). Furthermore, the progress towards their goal weight has a positive sign (θ_g), which suggests that users are motivated to work towards their long-term goal as they receive utility from making progress. Most importantly, we find that users receive positive utility from short-term goal accomplishment, in the form of adhering to their *past* daily budget of calories (θ_a), which suggest that past success may set the precedent for future successes. If we compare the short-run and long-run goal achievements, losing 10% of the weight an individual aims to lose in the long-run yields only about 16% of the utility gained from daily budget goal adherence. Taken together, these results further point to the importance of short-term goal achievement as a way to maintain a healthy lifestyle, in both an absolute and relative sense. In other words, the users appear to be more motivated by successes at adhering to the budget as opposed to progress towards their weight loss target. This finding is in fact consistent with Gollwitzer and Brandstätter (1997), who show in a laboratory setting that reinforcing implementation intentions are key

Figure 26: Implications of Hypothetically Reducing or Increasing Daily Budget of Calories



to self-regulation.

6.4 Implications on Daily Budget Design

We explore a hypothetical application design policy in this section. One important aspect of the application is the daily budget of calories c_{it}^*, as it affects the likelihood users are able to adhere to their short-term goal. There is a potential trade-off the application may face in setting the daily budget, as setting a high budget may make short-term goal achievement easier, but on the other hand, setting a higher budget would slow down the progression of weight loss progression as users may not cut as many calories from their diet.

To conduct our counterfactual analysis, we use the estimated model parameters, and then construct approximated value functions under various hypothetical policies regarding the daily budget. In particular, we look at slight deviations in the daily budget, ranging from a 5% decrease in the daily budget to a 5% increase in the daily budget. The average user's value function is an appropriate measure to evaluate this potential trade-off, as it would capture both the encouraging effects from short-term goal achievement as well as the longer-run effects on weight loss progress.

We consider two variants of this hypothetical policy. First, we look at a scenario in which this daily budget change is applied *uniformly* across all users. Second, we look at a scenario in which this daily budget change is *conditional* on whether the user was making progress towards his or her weight loss goal (i.e., $g_{it} > 0$). Figure 26 provides the results from our counterfactual analysis. Our results for the uniform policy show that as we allow for slight increases in the daily budget, the average user's long-run value also increases. That is, allowing for a *more generous* daily budget of calories seems to benefit users, overall. Notice also that the amount that the approximated value function increases is larger when we compare the 0% change to 1% change, as opposed to 1% change to 2% change, which suggests that gains from daily budget increases are concave. As for the policy that conditions on past progress towards weight loss goal, we see that in general, there is also an increase in the approximated value function as the daily budget increases slightly. However, we see that budget decreases are more beneficial to users, while budget increases are less beneficial to users when comparing conditional policies with uniform policies. In other words, this result suggests that the application should make short-term goals more ambitious only to those individuals who have seen past success in moving towards their long-term goal.

7 Conclusion

Our research uncovers evidence of a causal relationship between short-term and long-term goal achievement under the context of weight loss. Using novel data from a mobile weight loss application, we show via a regression discontinuity empirical strategy that short-term achievements in the form of staying within the recommended daily calories budget lead to higher levels of weight loss in the immediate and intermediate future. We show that the long-term success in weight loss from short-term goal achievement may be driven by the impact that these short-term achievements on future short-term achievements. Furthermore, we show that the mobile application would benefit from the users' sense of accomplishment as short-term achievement leads to greater adoption of the application's premium service.

Moreover, we demonstrate noticeable differences in the positive effect from short-term goal accomplishment depending on the user segment (i.e., gender, age, initial BMI, degree of struggle, ambitiousness of weight loss goal). We later demonstrate via structural estimation of a dynamic model that users receive positive utility from past short-term goal accomplishments, and using the estimated model, our counterfactual analysis reveals that slight increases to the daily budget of calories can benefit users (in the long-run), and that it may be worthwhile making budgets harder for those who have already made progress towards their long-term weight loss goal.

An immediate managerial implication of our findings is that any self-improvement service or application should adopt policies to set realistic short-term goals that their users can achieve. This way, users gain confidence and are more likely to continue achieving other short-term goals; and eventually, users will eventually reach their long-term goal. Specific to the mobile weight loss application industry, one suggested strategy would be for them to set more generous budget of calories to ensure that users are likely to stay within budget, or even better, adjust the budget of calories based on the user's past progress towards his or her weight loss target. They could then set more aggressive budgets as the user builds his or her confidence.

We currently focus on the customer development aspects of the mobile weight loss application (i.e., user upgrades to the paid premium services). However, customer lifetime value could also be affected by short-term goal achievement. It would make for an interesting trade-off for the firm, as users who are very successful at reaching their target may no longer need the application, but on the other hand, users who find no success may also quit using the application (albeit for the opposite reason).

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