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Gamification on Obese Children's BMI-derivative Outcomes, Physical Activity, and Sugar Sweetened Beverage Consumption

By

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Degree to be Awarded: Master of Science in Public Health

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Abstract

Gamification on Obese Children's BMI-derivative Outcomes, Physical Activity, and Sugar Sweetened Beverage Consumption

By Audrey Chang

Childhood obesity is a growing public health problem around the world. Mitigating this epidemic, especially through behavioral interventions, would aid not only children's health but alleviate economic burdens. Challenges to interventions in children's adiposity assessment are growing; secondary to these challenges, it is important to consider anthropometric measures such as body mass index (BMI kg/m^2) and its derivatives (e.g., BMI z-score). Here, we examine the effects of gamification on children using such measures, assess the association between BMI/change in BMI with sugar sweetened beverage (SSB) consumption/number of steps, and apply longitudinal analysis of change in steps and SSB per day by week.

We leveraged a pre-existing dataset from the Children's Hospital of Philadelphia and studied the effects of a gamification intervention by looking at the effects on daily steps, SSB consumption, weight, BMI, BMI z-score, BMI percentile and BMI % change in 10-16 years-olds. We tested within-arm and between-arm differences (arms are self-monitored, SM, and self-monitored plus gamification, SM + G). Correlation for change in steps and SSB consumption with change in BMI and Pre-Intervention BMI was also evaluated. Lastly, we fitted longitudinal mixed effect models for change in steps and SSB. For each model, arm, week, and their interaction plus *a priori* variables sex and age were included.

When using t-test, gamification effect was not significant for any of the BMI derivatives or weight (e.g. BMI mean(SD) = 0.665(1.588) in SM vs -0.187(1.077) in SM+G, p= 0.115). Additionally, there was no within-arm difference. Change in steps was not significant but change in SSB consumption was significant for weeks 3 and 6 when using a mixed model (week 3: 0.424(0.247) in SM vs -0.008(0.155) in SM+G, p= 0. 031; week 6: p= 0.015).

The only significant correlation was change in steps for SM week 3 (r = -0.939, p <0.001) vs change in BMI. For the model with change in steps as the outcome, mother's education and income were considered statistically significant with arm, week, their interaction, sex, and age. For change in SSB, the model included variables arm, week, their interaction, sex, age, and mother's employment.

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Table of Contents

1. Introduction……………………………………………………………………………….………..1

2. Methods

2.1 Introduction to Dataset……………………………………………………………...…3

2.2 Creating Variables…………………………………………….…..……………...5

2.3 Independent & Paired T-tests…………………………………….……………….5

2.4 Pearson Correlation…………………………………………..…………………..7

2.5 Longitudinal Mixed Effects Model…………………………………………………….7

3. Results

3.1 Summary Statistics………………………………………………..……………...9

3.2 Independent & Paired T-tests…………………………………………………….…..10

3.3 Pearson Correlation……………………………………………………………………..10

3.4 Longitudinal Mixed Effects Model………………………………………………...11

4. Discussion………………………………………………………………………….…………..12

5. Tables & Figures………………………………………………………………..………………15

6. References…………………………………………………………………………………...29

1. Introduction

Childhood obesity has been a major public health challenge; from 2007—2016, there has been an upward trend in obesity prevalence, especially for children aged 2-5 (Hales et al., 2018). Obesity has not only been linked with many co-morbidities, such as diabetes, heart disease, cancer, and mental health, but also creates an economic burden (Hruby & Hu, 2016).

While obesity poses a concern for both adults and the youth (Hruby & Hu, 2016), focusing on the younger generations may prove to reap larger benefits in the coming years. As obesity is a chronic disease, it was found that early development of high BMI is indicative of obesity into adulthood, especially those with severe obesity (Ward et al., 2017). Understandably, a projected 60% of those children will be obese when reaching the age of 35, when using the level of childhood obesity as of 2017, with predictions higher for 10-16 year olds (Ward et al., 2017). Between 2003-2008, over 30% of children between the ages of 2-19 had overweight (i.e., above the 85th BMI percentile, but below the 95th BMI percentile) and in 2015-2016, 18.5% had obesity (above the 95th BMI Percentile) (Hales et al., 2018; Kuczmarski et al., 2002;).

It is well-known that there are environmental (such as access to food stores and lifestyle factors) (Powell et al., 2007), socioeconomic, and genetic factors that contribute to the development of obesity. Encouragingly, lifestyle changes are modifiable and an effort to increase levels of physical activity and implement healthier diet should be prioritized. Improving on these factors could lead to decreased obesity prevalence (Hruby & Hu, 2016; Wing et al., 2001). However, implementation of these lifestyle changes has proven to be difficult. Behavioral interventions have proven to provide benefit children with overweight and obesity, but the effects may be short term (Whitlock et al., 2010). There have been many different sources of treatment over the past years, and in the more recent years there have been much more novel ideas for these treatments.

Strategies for treatment of this epidemic has have been wide-ranging, including family-based group treatment (Epstein et al., 2014), social media (Li et al., 2013), and gamification, which is described by King et al. as the “process of using ‘gaming’ elements i.e. achieving points and medals to motivate and engage people in non-gaming contexts” (Deterding et al., 2011; King et al., 2013). In general, technological advances have been considered as a worsening effect on health, such as by the lack of physical activity; but these same tools can be used to maintain or support lifestyle changes, or even enhance clinical practices. There seems to be a turn towards technology to not only help abate the obesity epidemic through virtual reality, gaming, and other tools such as smartwatches (Thomas & Bond, 2014), but also impact other behavior changes. This development in healthcare may be a way to improve communications with professionals, delivery of interventions, or record-keeping of our health. These include interventions using cell phones for treatment adherence (Lester et al., 2010) and smoking (Klasnja & Pratt, 2012).

.In addition to the intervention approach, effectiveness can also be determined by the obesity outcome measure selected. This is especially true in pediatric studies because children experience increases in their height and weight as a normal process of growth. Measuring adiposity in children, therefore, proves to be challenging when comparing studies within the same field. The BMI metric transformations (i.e., BMI z-scores and percentiles) from the Centers for Disease Control and Prevention (CDC) tend to provide a ceiling effect for those children with extreme BMIs, and thus create BMI z-scores that differed significantly amongst children with similar BMI and BMI percentiles (Freedman et al., 2017). Even so, certain BMI metric transformations may be preferable to others, depending on the type of study design. It was found that BMI percentile was useful for classification, BMI z-scores were more suited for cross-sectional adiposity assessment but tended to be a worse measure than BMI % change. BMI (kg/m^2 or % units) was found to be the best measure of adiposity change, but the advantages proven were small (Cole et al., 2005).

In this paper, we will examine the effects of a gamification intervention targeting increases in daily steps on weight and BMI in children. We will analyze multiple measures and derivatives of BMI (e.g., BMI z-score, BMI percentile, and BMI % change) and compare the results. We will also apply longitudinal analysis of change in number of steps and sugar sweetened beverages (SSB) per day by week for seven weeks. Lastly, an assessment of the association amongst daily SSB consumption, daily number of steps, weight and BMI will be evaluated. By focusing on children rather than adult in these aims, we are better able to serve this specific population and help subside the ever-increasing rate of global obesity.

2. Methods

2.1 Introduction to Dataset

The data are from a project completed at the Children's Hospital of Philadelphia (CHOP), courtesy of Dr. Elizabeth Parks Prout, that used the University of Pennsylvania's "Way to Health" online platform. This online platform was created in 2010, and provided an information technology infrastructure to conduct various studies (*Way to Health*, n.d.-a). These data were obtained in 2017 with the primary intent of determining whether gamification increases step count and decreases sugar sweetened beverage (SSB) intake in parent-child dyads with obesity (*Way to Health*, n.d.-b). Any parent was targeted, regardless of sex, but only mothers had enrolled. In this thesis we will focus on the children.

Participants were contacted by email in collaboration with CHOP's Pediatric Research Consortium. The eligibility criteria included: obesity (BMI $\geq 95^{th}$ percentile for age and sex), speak English, have a smartphone, and intake $\geq$ 2 SSB (12 oz/serving) per day for 10-16 year old children. Ineligibility factors included substance abuse, psychiatric diagnosis, syndromic obesity, having an eating disorder, and untreated depression/anxiety.

The daily steps were recorded with the Fitbit Flex 2, worn on the non-dominant hand. The daily step data was captured by the Fitbit application and streamed to Way to Health. For days with <300 steps, these observations were censored. The study design included a run-in week and participants were randomized into two arms: self-monitoring (SM) or self-monitoring with gamification (SM + G). All participants were given a step goal of 7,000 steps per week for the first week, based upon the 1-week run-in data and this increased by 250 steps the following weeks for eight weeks. All participants were also asked to sign a pledge of commitment to their goals. Those assigned to the SM + G arm, were awarded points and weekly medals for achieving the goals (Parks et al., 2019).

The details of gamification are as follows: all participants, regardless of arm assignment, received feedback of step goal achievement. For the SM + G arm, the participants were allocated 70 points every Monday with 10 points deducted if the step goal was not achieved (none were deducted if the goal was met). Should the participant earn ≥ 50 points at the end of the week (i.e., met the step goal five or more times in a week), he/she would progress to the next medal level (bronze, silver, then gold). Otherwise, the participant would regress levels. The participants in this arm were also provided motivational messages (Parks et al., 2019).

SSB consumption was self-reported via text message, and gamification was not used with an SSB goal. A text was sent at 7 pm every night, asking for number of SSB servings consumed that day (i.e., a serving being 12 oz.). The text messages were sent and received by Way to Health using Twilio. An acknowledgement of daily SSB intake was provided (Parks et al., 2019).

Height (cm) and weight (kg) were measured at pre-intervention and post-intervention. Each of these measures were taken in triplicate and an average was then calculated. From those averages, the BMI was determined, for pre-intervention and post-intervention, where

$$BMI = \frac{\text{kg}}{m^2}$$

Raw data was obtained from REDCap, a web application used to manage surveys and databases, for weight and BMI, as well as the variables considered for the longitudinal mixed models (as described in section 3.5). For variables that were not included in the data obtained from REDCap, a cleaned dataset was received on December 18, 2019, with repeated measures for each participant by week. These weeks are from 0 (i.e., run-in) to week 7. For future studies following this thesis, we will access and work with only the raw dataset.

2.2 Creating Variables

Data analysis was conducted using SAS 9.4 Software. We considered five different BMI outcomes: weight (kg), BMI (kg/m^2), BMI z-score (using CDC 2000 reference data), BMI percentile (using CDC 2000 reference data) and BMI (kg/m^2) % change. The BMI % change was calculated as:

$$\frac{post\ intervention\ BMI - pre\ intervention\ BMI}{pre\ intervention\ BMI} * 100$$

To obtain the adjusted BMI z-score and percentiles, we obtained the SAS program from the CDC for the 2000 CDC growth charts for children ages 0 to < 20 years old. The BMI z-scores and percentiles (as well as the standard deviations) were calculated and adjusted for each child's sex and age. It should be noted that the World Health Organization (WHO) also has charts which are recommended for children under 2 years old (Kuczmarski et al., 2002).

2.3 Independent & Paired T-tests

The change in weight, BMI and BMI derivatives by week of intervention were compared to the Pre-Intervention weight, BMI and BMI derivatives, the pre-intervention measurements being taken before the run-in period. These differences between pre-intervention and post-intervention collection for weight, BMI, BMI z-score, BMI percentile and BMI % change were first assessed using paired t-tests for within group changes as well as the independent t-test for between group changes. We used α = 0.01 to test significance to adjust for the multiple tests performed.

The paired t-test was used to assess the within arm differences. For the paired t-test, we were interested in the before and after effects within each arm (SM and SM + G The t value was found by finding the change in the weight, BMI, or BMI derivative variables for each arm, then assessing significance in the difference in pre-intervention and post-intervention:

$$t = \frac{\overline{x}_{diff} - 0}{s_{\overline{x}}}$$

where $s_{\overline{x}} = \frac{s_{diff}}{\sqrt{n}}$

$\overline{x}_{diff}$ represents the mean of the difference between post-intervention and pre-intervention, and s_{diff} represents the standard deviation of the difference; $\sqrt{n}$ is the square root of the size of the number of participants. The degrees of freedom for this test is $n - 1$.

The independent t-test statistic was calculated to assess for between-arm differences and is calculated by:

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{S^2}{n_1} + \frac{S^2}{n_2}}}$$

Where $\overline{x_1}$, $\overline{x_2}$ represent the change in weight, BMI, or BMI measures of SM and SM + G, respectively, n_1 and n_2 are the number participants in the groups, and S^2 is an estimator of the variance and can be calculated as follows:

$$S^2 = \frac{\sum(x - \overline{x_1})^2 + \sum(x - \overline{x_2})^2}{n_1 + n_2 - 2}$$

2.4 Pearson Correlation

To assess the association between change in SSB and change steps against BMI change as well as pre-intervention BMI, we used the Pearson correlation:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

Where $cov(X,Y)$is covariance of X and Y and σ_X, σ_Y are the standard deviations of X and Y, respectively. In this thesis, X would be either the change in SSB or the change in steps, and Y is BMI or the change in BMI. We calculated the overall correlation as well as the correlation by arm. We also assessed Spearman correlation, but first evaluated if Pearson followed the normality assumption.

Looking at the correlation helps us examine the change in correlation as the weeks progress. We looked at the change in SSB and steps vs. BMI or the change in BMI for each week compared to week 1. The change in SSB and steps subtracted the week i from week 1, where $i = 1, \dots, 7$. The change in BMI subtracted the post-intervention BMI from the pre-intervention BMI, weekly BMI data does not change at a rate that would be readily detectable from week to week. We used $\alpha = 0.01$ to test significance to adjust for the multiple t-tests performed.

2.5 Longitudinal Mixed Effects Models

To account for the correlation between weekly data and for varying number of visit completed each week, longitudinal mixed effects models for change in SSB and change in steps were fit utilizing restricted (residual) maximum likelihood (REML) estimation with an unstructured covariance matrix via PROC MIXED in SAS. We discarded the run-in data for the change in steps and SSB consumption, since steps are likely to be increased from the novelty of a wearable device (Patel et al., 2017). Each mixed effects model contained arm, week, and their interaction along with *a priori* variables sex and age. Then other variables were considered based on backward elimination.

Sex and age of the child were also included as *a priori* variables, as they are known to be common variables in not only behavioral/ psychological studies (Emen & Aslan, 2019; Schwenck et al., 2014) but in many other research areas as well. Literature has distinguished differences in age and sex, especially when considering studies on children who may be at different stages of puberty. To assess the fit of the mixed models and to choose the best model possible, we used a significance level of $\alpha = 0.05$.

Our general random-intercept model is as follows:

$$y = \beta_0 + \theta_i + x_{ij}' \beta + \epsilon$$

$$\theta_i \sim^{iid} N(0, \tau^2)$$

where y is the change from week 1 in steps or SSB consumed, x_{ij}' is the vector of statistically significant demographic covariates and β is the corresponding vector of regression coefficients, θ_i is the difference between each individual-specific baseline and β_0, β_0 is the overall baseline change in steps or SSB, and τ^2 is the variation of baseline between children.

For variable selection, we used backwards elimination. We started with a model that included arm, week, the interaction variable of arm and week, sex, mother's income, mother's employment, mother's education, and mother's marital status. We then used $\alpha = 0.0.5$ as the cut-off for significance.

Before model selection, we assessed multicollinearity by evaluating the Variable Inflation Factors (VIFs) of the covariates, where a VIF > 10 indicates multicollinearity. The Differences of Means p-values from the mixed models were also compared to the between-arm t-test p-values; the means from PROC MIXED were compared to the PROC MEANS to assess differences between the two methods.

3. Results

3.1 Summary Statistics

The sample was comprised of 38 children, 34 of which were black. There were 23 males and 15 females with an average age of 13 years, ranging from 11 to 16 years. At baseline, the children's average daily steps were 7,233 and on average drank 1.25 sugar sweetened beverages (SSB) a day. The average weight was 85.25 kg, BMI averaged 32.62, height averaged 160.94 cm, BMI z-score averaged 2.38 and the average BMI percentile was 98.02. Most of the mothers of the participants were employed, about half had not completed college, the income was evenly distributed amongst the categories, and about half were married [Table 1].

The distributions of each variable (i.e., race, sex, age, daily steps, daily SSB consumption, height, weight, BMI z-score, BMI % change, BMI Percentile, Mother's Income, Mother's Employment, Mother's Education, and Mother's Marital Status) are similar. The most notable difference is the number of participants in each arm. For self-monitoring (SM), there were 15 participants, while for self-monitoring with gamification (SM + G) there were 21 participants [Table 1].

The rates in which the participants reported their data or had their data collected through the Fitbit varied week to week and by arm. At best, 87% of the SM arm reported data for week 1, and at worst only seven of the 21 participants in the SM + G arm reported data for week 7 [Table 2, 3]. There were about the same number of participants who provided one week's worth of data as there were with seven weeks.

The run-in data was also discarded in the analyzation of thesis, as it was a week of screening to ensure that the participants would provide reliable baseline observations to compare to the different measures (i.e., weekly change in SSB and Steps).

3.2 Independent & Paired T-tests

The first part of this thesis was to determine a change in weight, BMI, or the different BMI measures (BMI z-score, BMI percentile and BMI % change), both between and within arms. We found that for both within and between measures, gamification had no effect at the $\alpha = 0.05$ level. For between-arm p-values, they ranged from $p = 0.11$ to $p = 0.91$, while the p-values for within-arm had a smaller range ($p = 0.13$ to 0.60 for SM, and $p = 0.31$ to 0.54 for SM + G). Most of the change in weight and BMI measures were positive, except for BMI and BMI % change [Table 4].

3.3 Pearson Correlation

To assess the association between change in SSB and change steps against both BMI and BMI change, we used the Pearson correlation. The distribution of the plots change variables are approximately normal, indicating that Pearson correlation is appropriate. Since there were no statistically significant change for any of the different BMI measures, we used BMI change for evaluating correlation.

Using $\alpha = 0.01$, the Pearson correlations between the change in steps in relation to week 1 and change in BMI (post-intervention BMI – pre-intervention BMI) was statistically significant for week 3 for SM ($r = -0.939$, $p < 0.001$). When compared to pre-intervention BMI, none of the weeks or arms showed significant correlation. Most correlations show a negative correlation between change in steps and change in BMI [Table 7], but is almost equally positive and negative when change in steps was compared to pre-intervention BMI [Table 8].

For change in SSB, none of correlations were statistically significant when compared to pre-intervention BMI nor change in BMI. In contrast with the change in steps from Table 10, the correlations for change in SSB against change in BMI had a mix of positive and negative correlations, but were all negative for SM + G [Table 15]. For pre-intervention, the correlations were all negative for SM and were all positive for SM + G [Table 16].

3.4 Longitudinal Mixed Effects Models

To create a longitudinal mixed effects model for change in SSB and change in steps, we constructed a random effect mixed model with an unstructured covariance matrix. We discarded the run-in data for the change (from week 1) in steps and SSB consumption. Both models, change in SSB and change in steps, contained arm, week, and their interaction along with a prior variables sex and age. The variables considered for backwards elimination included mother's education, mother's income, mother's marital status, and mother's employment status. Then other variables were considered based on backward elimination. These four characteristics were included in the primary paper's Baseline Characteristics Table and hence were used in constructing the models for this thesis.

There were no Variable Inflation Factors (VIFs) above three, indicating that multicollinearity was not an issue here [Table 5]. Using backwards selection with $\alpha = 0.05$ the model for change in steps, it was found that of the variables considered for backwards elimination, mother's income ($p = 0.0009$) and mother's education (0.0061) were significant [Table 9, 10]. The final variables in the model include: Arm, week, arm*week, age, sex, mother's education and mother's income [Table 10]. The difference in means between the two arms for change in steps were not significant at the $\alpha = 0.05$ level [Table 12].

We used the same methods of model selection for change in SSB consumption and found that mother's employment ($p = 0.0042$) was a significant fixed effect [Table 17, 18], when adjusting for the design variables (arm, week, interaction) and *a priori* variables (sex, age). At the $\alpha = 0.05$ level, the difference in means between the two arms were significant for week 3and 6 (mean difference(SE) = 0.661(0.288), $p = 0.031$; 1.156(0.438), $p=0.015$, respectively).

The average number of weekly steps and weekly SSB consumed can be shown in Figure 1 and 4, and the change in steps and SSB from week 1 can be seen in Figure 2 and 3, and 5 and 6., It can be seen that there was a decrease for both daily steps as well as change in steps, starting with week 5.

4. Discussion

In this thesis, we explored the effects of a gamification intervention for step promotion on childhood obesity through five different measures (weight, BMI, BMI z-score, BMI percentile and BMI % change) for in-between differences as well as within-arm differences and assessed whether different anthropometric measures deliver similar results. Correlation between change in steps or change in sugar sweetened beverages (SSB) against pre-intervention BMI or change in BMI was also examined. Lastly, we created longitudinal random effects mixed models for change in steps and change in SSB.

There was no significant effect of the gamification step intervention on childhood weight, BMI, BMI Percentile, BMI z-score, or BMI % change. While all of the anthropometric measures yielded the same conclusion, there was a wide range of p-values. Overall, there was not enough power to detect changes in the anthropometrics. Although none of these changes were significant, some variables with lower p-values (such as weight or BMI) are more sensitive, while variables like the change in BMI z-score may be more difficult to detect. Additionally, there was only some weeks that had significant correlation between change in steps or SSB vs pre-intervention BMI or BMI change.

It is understood that clinically meaningful for behavioral changes does not always strictly follow the statistical norm of $\alpha = 0.05$. After speaking with Drs. Parks Prout and Mitchell, both of whom were Principal Investigators, it was decided that what was clinically significant was an increase of 250-step count per week, or an average reduction of half a 12 oz serving of SSB per day. Overall, steps increased ≥ 250 steps from week 1 for weeks 2-5, for SM weeks 2-6, and weeks 2-4 for SM + G; steps decreased otherwise [Table 6]. For SSB, there was not a reduction of half a serving of SSB per day at all, therefore yielding no clinically meaningful significance [Table 14]. However, it's important to be cautious when using self-reported data, whether it be from children or adults.

The most significant obstacle in this dataset were the sparsity of data. With $n = 38$, there was trouble with modelling as well as the reliability of our results. When running the model for change in steps, we received this warning from SAS: Convergence criteria met but final Hessian is not positive definite. This could be from a misspecified models or that the sample is too small (Kiernan et al., 2012). Certainly, the residuals for the change in steps were cone-shaped, indicating heteroscedasticity. This heteroscedasticity may have been from the sparsity of data. Additionally, the change in steps p-value between arms differed greatly when using t-test vs when using PROC MIXED ($p = 0.237$ for t-test, $p = 0.788$ for PROC MIXED) [Table 6]. This too may be due to sparsity of data and an issue of power for the t-test.

Not only was our starting $n = 38$ small, but there were missing data. Some of the participants' data for arm assignment were missing, or were mis-assigned (in this thesis, we used intend-to-treat). Additionally, many datapoints for the 7 weeks were not reported from the participants. Even as this is not uncommon for self-reporting, having a lack of data hinders the findings of any study. These drops in reporting could have been from lack of response from the participants (e.g.., they grew tired of having to report their SSB intake daily), or that the novelty of the Fitbit was wearing off. Additionally, we did not have access to the raw data for some of the data needed for this thesis.

When comparing the means using two different procedures in SAS (PROC MEANS vs LSMeans in PROC MIXED), it could be seen that there was disagreement in the two procedures for both steps and SSB [Table 13, 21]. The MEANS procedure is computed by summing all points and dividing by total number of points, whereas the LSMeans (i.e., Least Squares Means) is a linear sum of the estimated effects. The differences may be due to the missing values in the dataset, especially when considering our use of change in steps or change in SSB, or due to potential lack of normality in the mixed models.

We also had to adjust α to $\alpha = 0.01$ for multiple testing for t-tests as well as the tests for correlation. In future research, it would be advised to use ANOVA to test the statistical significance of the between and within arm differences instead of separate t-test for within (paired) and between (differences), as well as examining whether the change from the run-in period agrees with change from week 1, and to model values at each time point in addition to change from week 1.

5. Tables & Figures

Table 1: Adolescent Baseline Covariates [Count n(%) or Mean(SD)]			
	Overall	**SM**	**SM + G**
Variables	**N total: 38**	15	21
Race	White: 2(5.26%) Black: 34(89.47%) Native American: 1(2.63%) Other: 1(2.63%)	White: 1(6.67%) Black: 14(93.33%) Native American: 0(0%) Other: 0(0%)	White: 1(4.76%) Black: 18(85.71%) Native American: 1(4.76%) Other: 1(4.76%)
Sex	Male: 23(60.53%) Female: 15(39.47%)	Male: 7(46.67%) Female: 8(53.33%)	Male: 7(33.33%) Female: 14(66.67%)
Age	13.29 (2.10)	12.13(2.07)	13.40 (2.01)
Daily Steps/week	7,223 (4,276.47)	7,017 (4,753.81)	7,414 (3,954.02)
Daily SSB/week	1.29 (0.99)	1.05 (0.77)	1.39 (1.11)
Height (cm)	160.94 (8.42)	157.30 (9.42)	163.63 (7.03)
Weight (kg)	85.25 (21.92)	86.40 (27.19)	84.5 (16.23)
BMI	32.62 (6.46)	34.33 (7.49)	31.40 (4.71)
BMI z-score	2.21 (0.39)	2.37 (0.33)	2.10 (0.34)
BMI % change	0.41% (4.05%)	N/A	N/A
BMI Percentile	98.02% (1.69%)	98.84% (0.83%)	97.71% (1.67%)
Mother's Income < $40,000 $40,001 - $69,999 $70,000+	 12(31.58%) 15(39.47%) 11(28.95%)	 5(33.33%) 7(46.67%) 3(20.0%)	 7(33.33%) 6(28.57%) 8(38.10%)
Mother's Employment Full-time Not full-time	 32(84.21%) 6(15.79%)	 15(100%) 0(0%)	 16(76.19%) 5(23.81%)
Mother's Education Some college or less 4-year degree Professional degree	 20(52.63%) 9(23.68%) 9(23.68%)	 7(46.67%) 3(20.0%) 5(33.33%)	 11(52.38%) 6(28.57%) 4(19.05%)
Mother's Marital Status Married Divorced/Widowed Never Married	 18(47.37%) 7(18.42%) 13(34.21%)	 7(46.67%) 5(33.33%) 3(20.0%)	 11(52.38%) 1(4.76%) 9(42.86%)

Note: In the data received, two participants were missing arm assignments

Table 2: Number (%) of Data Points Available in SM Arm: N = 15		
Week	**SSB n(%)**	**Steps n(%)**
Run-in	9 (60%)	12 (80%)
Week 1	12 (80%)	13 (86.7%)
Week 2	12 (80%)	11 (73.3%)
Week 3	11 (73.3%)	12 (80%)
Week 4	11 (73.3%)	9 (60%)

Week 5	11 (73.3%)	9 (60%)
Week 6	10 (66.7%)	6 (40%)
Week 7	6 (40%)	7 (46.7%)

Table 3: Number (%) of Data Points Available in SM + G Arm: N = 21		
Week	**SSB n(%)**	**Steps n(%)**
Run-in	5 (23.8%)	19 (90.5%)
Week 1	17 (81.0%)	14 (66.7%)
Week 2	17 (81.0%)	14 (66.7%)
Week 3	14 (66.7%)	12 (57.1%)
Week 4	14 (66.7%)	15 (71.4%)
Week 5	13 (61.9%)	13 (61.9%)
Week 6	12 (57.1%)	10 (47.6%)
Week 7	7 (33.3%)	7 (33.3%)

Table 4: T-Test Results of Difference (Post- Intervention – Pre-Intervention) in Weight & BMI Measures Within and Between Arms					
Measure	**Δ SM**	**Within p-value**	**Δ SM + G**	**Within p-value**	**Between p-value**
Weight	1.9167	0.126	0.4646	0.544	0. 276
BMI	0.6651	0.218	-0.1873	0.497	0. 115
BMI Percentile	0.0927	0.601	0.1906	0.309	0.714
BMI z-score	0.0332	0.398	0.0264	0.521	0. 908
BMI % change	2.0003%	N/A	-0.4624 %	N/A	0. 148

Notes: for within difference, we used a paired t-test
for between difference, we used a 2-sample independent t-test
$\alpha = 0.01$ to account for multiple testing

Table 5: Covariate VIFs for Change in SSB and Steps		
Covariate	SSB	Steps
Week	1.005	1.042
Arm	1.571	1.500
Age	1.443	1.754
Sex (Male)	1.238	1.465
Income ($40,000-$70,000)	1.951	2.113
Income ($70,000+)	2.173	2.601
Employment (Full-time)	1.711	1.811
Degree (Professional)	1.310	1.574
Degree (4-year)	1.304	1.400
Marital Status (Never Married)	1.5556	1.620
Marital Status (Separated, Divorced, Widowed)	1.438	1.379

Table 6: Adolescent Daily Steps by Week [Mean(SE)]								
Week	**Overall**		**SM**		**SM + G**			
	Steps/ day	Δ from Week 1	Steps/ day	Δ from Week 1	Steps/ day	Δ from Week 1	t-test Between Group P-value	Difference in LS Means Between Group P-value
1	7223 (823)	N/A	7017 (1319)	N/A	7381 (1057)	N/A	N/A	N/A
2	7474 (662)	651 (609)	7209 (1052)	355 (992)	7414 (876)	923 (768)	0.652	0.469
3	8114 (899)	983 (836)	8241 (1411)	1027 (1340)	7988 (1177)	929 (978)	0.955	0.644
4	7645 (744)	608 (962)	7561 (1101)	724 (1193)	7695 (1020)	521 (1472)	0.920	0.864
5	6878 (740)	399 (873)	7182 (920)	1887 (1123)	6666 (1106)	-819 (1216)	0.126	0.228
6	6757 (1018)	-331 (924)	7,944 (1,457)	1485 (1689)	6,045 (1,381)	-1692 (792)	0.088	0.117
7	5129 (949)	-1746 (1266)	5172 (967)	-435 (1623)	5,086 (1723)	-3582 (1896)	0.237	0.788

Table 7: Pearson Correlation Coefficient *r* for Change in BMI with Change in Steps						
Week Compared to Week 1	**Overall**		**SM**		**SM + G**	
	r	P-value	*r*	p-value	*r*	p-value
2	-0.392	0.108	-0.725	0.027	-0.013	0.974
3	-0.260	0.314	-0.939	<0.001	0.493	0.215
4	-0.387	0.139	-0.859	0.013	-0.101	0.796
5	-0.027	0.918	-0.564	0.146	0.073	0.852
6	-0.128	0.676	-0.548	0.260	0.335	0.463
7	-0.349	0.293	-0.622	0.136	0.481	0.519

Note: $\alpha = 0.01$ to account for multiple testing

Table 8: Pearson Correlation Coefficients *r* for Pre-Intervention BMI with Change in Steps						
Week Compared to Week 1	**Overall**		**SM**		**SM + G**	
	r	P-value	*r*	p-value	*r*	p-value
2	0.098	0.656	0.332	0.319	-0.193	0.547
3	-0.031	0.893	0.049	0.881	-0.245	0.495
4	0.283	0.214	0.621	0.074	0.057	0.860
5	0.221	0.348	0.145	0.709	0.155	0.648
6	-0.075	0.798	-0.238	0.650	-0.395	0.333
7	0.167	0.604	0.297	0.517	-0.349	0.565

Note: $\alpha = 0.01$ to account for multiple testing

<table>
<tr><th colspan="5">Table 9: Model Selection Process for Change in Steps</th></tr>
<tr><th>Variables</th><th>Variable with largest p-value</th><th>F-value</th><th>p-value</th><th>AIC</th></tr>
<tr><td>Arm
Week
Arm*Week
Age
Sex
Mother’s Income
Mother’s Employment
Mother’s Education
Marital Status</td><td>Mother’s Employment</td><td>0.66</td><td>0.423</td><td>1864.1</td></tr>
<tr><td>Arm
Week
Arm*Week
Age
Sex
Mother’s Income
Mother’s Education
Marital Status</td><td>Marital Status</td><td>0.89</td><td>0.431</td><td>1821.1</td></tr>
</table>

Table 10: Type 3 Tests of Fixed Effects for Change in Steps				
Effect	**Num DF**	**Den DF**	**F Value**	**p-value**
Arm	1	17	0.11	0.748
Week	5	17	2.38	0.082
Arm*Week	5	17	2.56	0.066
Age	1	17	0.00	0.996
Sex	1	17	8.64	0.009
Mother’s Education	2	17	6.99	0.006
Mother’s Income	2	17	10.96	<0.001

<table>
<tr><th colspan="4">Table 11: Least Squares Means for Change in Steps</th></tr>
<tr><th>Variable</th><th></th><th>Estimate</th><th>Standard Error</th></tr>
<tr><td>Arm</td><td>SM
SM+G</td><td>130.69
-308.04</td><td>934.37
989.69</td></tr>
<tr><td>Week</td><td>2
3
4
5
6
7</td><td>193.94
1065.21
449.89
-17.397
-317.77
-1905.94</td><td>658.68
948.53
991.59
834.16
608.69
1229.95</td></tr>
</table>

Arm*Week	SM	2	-282.47	891.41
	SM	3	628.04	1271.97
	SM	4	279.57	1433.06
	SM	5	1014.66	1188.27
	SM	6	722.17	886.51
	SM	7	-1577.84	1647.27
	SM + G	2	670.34	948.04
	SM + G	3	1502.39	1382.55
	SM + G	4	620.22	1354.26
	SM + G	5	-1049.45	1158.17
	SM + G	6	-1357.7	863.73
	SM + G	7	-2234.05	1789.32
Sex	Female		1158.24	757.61
	Male		-1335.6	856.83
Mother's Education	Some college or less		-895.5	704.22
	4-year degree		-1713.62	908.59
	Professional Degree		2343.08	1063.42
Mother's Income	< $40,000		-2965.7	1102.37
	$40,000-$70,000		1928.81	788.85
	> $70,000		770.86	845.48

Table 12: Differences of Least Squares Means between SM and SM + G for Change in Steps

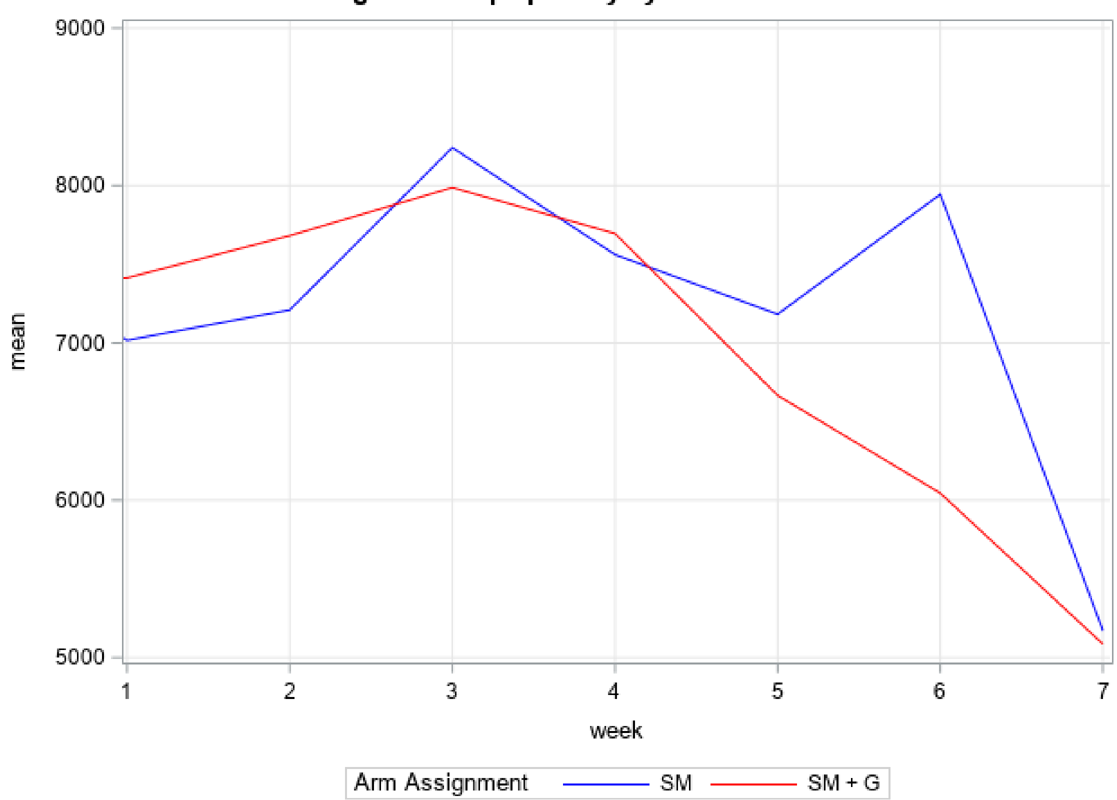
Δ from Week 1	Mean Difference (SE)	95% CI of Mean Difference	Difference p-value
2	-952.82 (1285.04)	(-3664.02, 1758.39)	0.4685
3	-874.35 (1860.08)	(-4798.77, 3050.07)	0.6443
4	-340.65 (1960.2)	(-4476.3, 3795)	0.8641
5	2064.12 (1650.27)	(-1417.65, 5545.88)	0.228
6	2079.86 (1257.73)	(-573.72, 4733.44)	0.1165
7	656.2 (2404)	(-4415.79, 5728.2)	0.7882

Table 13: Comparing Proc Means & Proc Mixed LSMeans for Change in Steps

Variable		**PROC MEANS Mean(SE)**	**PROC MIXED LSMEANS Mean(SE)**
Week	2	651.29 (609.49)	193.94 (658.68)
	3	982.53 (836.47)	1,065.21 (948.53)
	4	607.89 (962.08)	449.89 (991.59)
	5	398.86 (872.99)	-17.397 (834.16)
	6	-330.85 (923.8)	-317.77 (608.69)
	7	-1,746.43 (1,265.54)	-1,905.94 (1229.95)

Arm*Week	SM	2	354.99 (992.19)	-282.47 (891.41)
	SM	3	1027 (1340.47)	628.04 (1,271.97)
	SM	4	724.24 (1193.47)	279.57 (1,433.06)
	SM	5	1887.1 (1122.99)	1,014.66 (1,188.27)
	SM	6	1484.53 (1688.94)	722.17 (886.51)
	SM	7	-435.05 (1623.07)	-1,577.84 (1,647.27)
	SM + G	2	922.9 (767.88)	670.34 (948.04)
	SM + G	3	929.16 (977.61)	1,502.39 (1,382.55)
	SM + G	4	520.63 (1471.91)	620.22 (1,354.26)
	SM + G	5	-818.8 (1215.66)	-1,049.45 (1,158.17)
	SM + G	6	-1692.38 (792.14)	-1,357.7 (863.73)
	SM + G	7	-3582.37 (1895.71)	-2,234.05 (1,789.32)

Figure 1: Steps per day by Week for each Arm



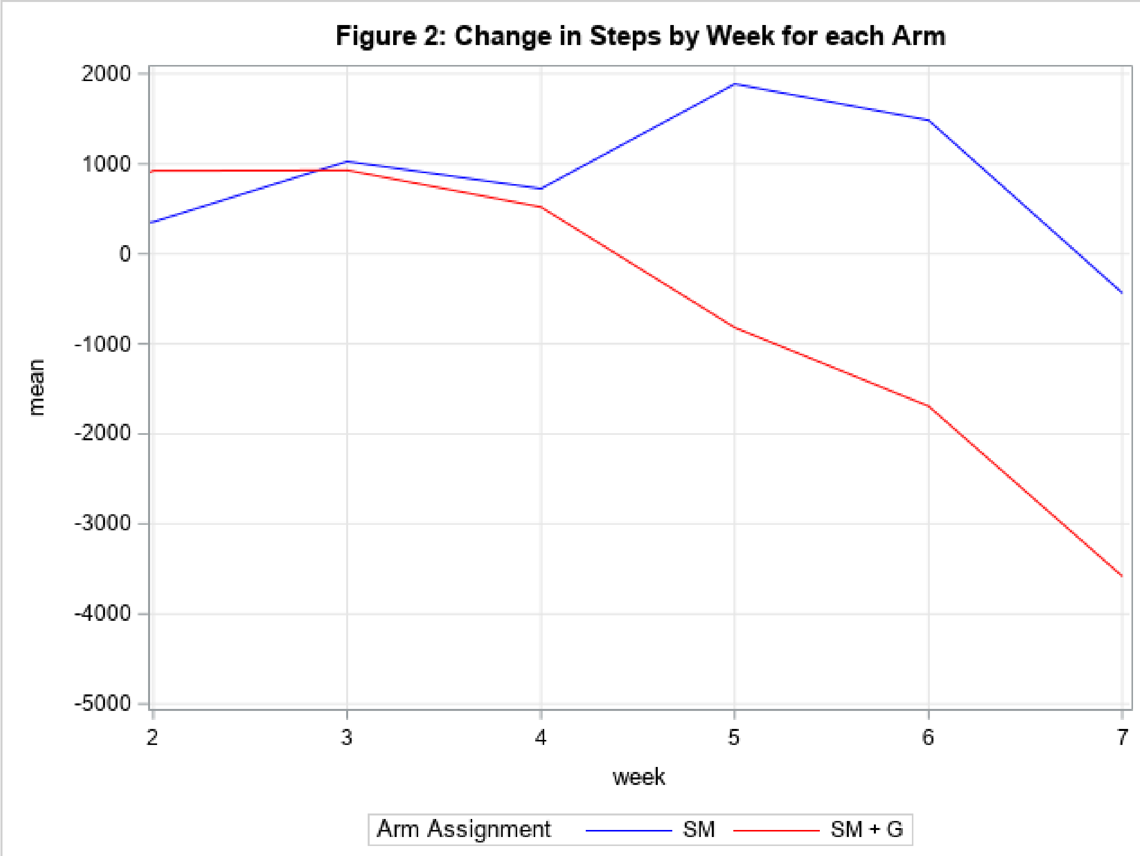


Figure 2: Change in Steps by Week for each Arm
2000
1000
0
-1000
-2000
-3000
-4000
-5000
mean
2
3
4
5
6
7
week
Arm Assignment
SM
SM + G

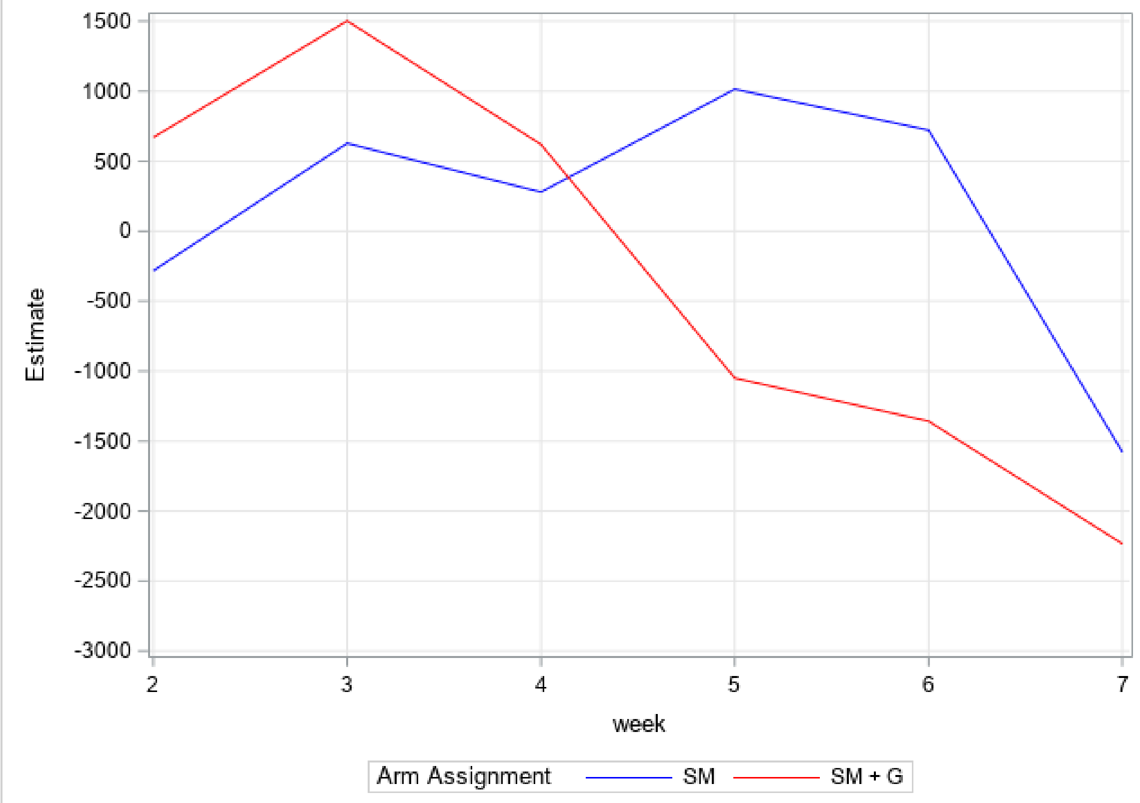


Figure 3: Change in Steps using LSMeans in Proc Mixed

Table 14: Adolescent Daily SSB by Week [Mean(SE)]								
Week	**Overall**		**SM**		**SM + G**			
	SSB/ day	Δ from Week 1	SSB/ day	Δ from Week 1	SSB/ day	Δ from Week 1	t-test Between Group P-value	Difference in LS Means Between Group P-value
1	1.294 (0.181)	N/A	1.052 (0.265)	N/A	1.388 (0.268)	N/A	N/A	N/A
2	1.301 (0.179)	0.071 (0.099)	1.129 (0.223)	0.077 (0.145)	1.404 (0.276)	0.133 (0.130)	0.778	0.448
3	1.183 (0.170)	0.126 (0.148)	1.344 (0.286)	0.424 (0.247)	1.045 (0.226)	-0.008 (0.155)	0.136	0.031
4	1.209 (0.174)	0.195 (0.139)	1.252 (0.295)	0.332 (0.280)	1.176 (0.217)	0.087 (0.119)	0.434*	0.073
5	1.209 (0.207)	0.152 (0.199)	1.161 (0.285)	0.059 (0.346)	1.249 (0.306)	0.230 (0.234)	0.679	0.422
6	1.191 (0.210)	-0.005 (0.301)	1.535 (0.326)	0.5281 (0.307)	0.904 (0.256)	-0.450 (0.463)	0.108	0.015
7	1.154 (0.317)	0.230 (0.321)	1.333 (0.558)	0.446 (0.591)	1.000 (0.378)	0.044 (0.347)	0.555	0.278

Note: * indicates unequal variance

Table 15: Pearson Correlation Coefficients r for Change in BMI with Change in SSB						
Week Compared to Week 1	**Overall**		**SM**		**SM + G**	
	r	P-value	r	p-value	r	p-value
2	-0.102	0.637	0.063	0.871	-0.199	0.494
3	-0.060	0.785	0.072	0.854	-0.333	0.266
4	0.049	0.826	0.123	0.753	-0.192	0.511
5	-0.194	0.400	-0.197	0.640	-0.122	0.691
6	0.065	0.793	0.147	0.729	-0.029	0.932
7	0.340	0.256	0.564	0.244	-0.065	0.890

Note: $\alpha = 0.01$ to account for multiple testing

Table 16: Pearson Correlation Coefficients for Pre-Intervention BMI with Change in SSB						
Week Compared to Week 1	**Overall**		**SM**		**SM + G**	
	r	P-value	r	p-value	r	p-value
2	-0.198	0.303	-0.303	0.338	0.161	0.552
3	0.105	0.611	-0.036	0.916	0.562	0.037
4	-0.038	0.855	-0.394	0.230	0.553	0.040
5	-0.015	0.944	-0.260	0.440	0.395	0.182
6	0.049	0.828	-0.687	0.028	0.322	0.308
7	0.124	0.688	-0.229	0.662	0.627	0.132

Note: $\alpha = 0.01$ to account for multiple testing

Table 17: Model Selection Process for Change in SSB				
Variables	**Variable with largest p-value**	**F-value**	**p-value**	**AIC**
Arm Week Arm*Week Age Sex Mother's Income Mother's Employment Mother's Education Marital Status	Mother's Education	0.20	0.820	260.0
Arm Week Arm*Week Age Sex Mother's Income Mother's Employment	Marital Status	1.15	0.336	257.7

Marital Status				
Arm Week Arm*Week Age Sex Mother's Income Mother's Employment	Mother's Income	1.51	0.244	257.3

Table 18: Type 3 Tests of Fixed Effects for Change in SSB				
Effect	**Num DF**	**Den DF**	**F Value**	**p-value**
Arm	1	23	4.06	0.056
Week	5	23	0.22	0.949
Arm*Week	5	23	13.32	<.0001
Age	1	23	9.98	0.004
Sex	1	23	21.92	<0.001
Mother's Employment	1	23	10.08	0.004

Table 19: Least Squares Means for Change in SSB				
Variable			**Estimate**	**Standard Error**
Arm	SM		0.5548	0.2374
	SM + G		-0.02588	0.1983
Week	2		0.3059	0.129
	3		0.3374	0.1631
	4		0.241	0.1802
	5		0.1653	0.2325
	6		0.1838	0.2358
	7		0.3534	0.2544
Arm*Week	SM	2	0.3861	0.1841
	SM	3	0.668	0.2372
	SM	4	0.547	0.2629
	SM	5	0.3446	0.3411
	SM	6	0.7616	0.3412
	SM	7	0.6215	0.3753
	SM + G	2	0.2257	0.1448
	SM + G	3	0.006778	0.1963
	SM + G	4	-0.06491	0.2206
	SM + G	5	-0.01412	0.2965
	SM + G	6	-0.3941	0.301
	SM + G	7	0.08534	0.3242
Sex	Female		0.5761	0.176
	Male		-0.04716	0.179

Mother's Employment	Full-time Not full-time	-0.08364 0.6126	0.145 0.2391

Table 20: Differences of Least Squares Means between SM and SM + G for Change in SSB			
Δ from Week 1	Mean Difference (SE)	95% CI of Mean Difference	Difference p-value
2	0.1604 (0.2078)	(-0.2695, 0.5903)	0.448
3	0.6612 (0.2884)	(0.06458, 1.2578)	0.0314
4	0.6119 (0.3251)	(-0.06076, 1.2845)	0.0726
5	0.3588 (0.4384)	(-0.5482, 1.2657)	0.4216
6	1.1557 (0.4378)	(0.2501, 2.0612)	0.0146
7	0.5362 (0.4826)	(-0.4622, 1.5346)	0.2781

Table 21: Comparing Proc Means & Proc Mixed LSMeans for Change in SSB				
Variable			**PROC MEANS Mean(SE)**	**PROC MIXED LSMEANS Mean(SE)**
Week		2	0.0708 (0.09943)	0.3059 (0.129)
		3	0.12619 (0.14817)	0.3374 (0.1631)
		4	0.19476 (0.13879)	0.241 (0.1802)
		5	0.15169 (0.19928)	0.1653 (0.2325)
		6	-0.00541 (0.30136)	0.1838 (0.2358)
		7	0.22967 (0.32054)	0.3534 (0.2544)
Arm*Week	SM	2	0.07721 (0.14455)	0.3861 (0.1841)
	SM	3	0.42403 (0.24709)	0.668 (0.2372)
	SM	4	0.33203 (0.27992)	0.547 (0.2629)
	SM	5	0.05909 (0.34637)	0.3446 (0.3411)
	SM	6	0.5281 (0.30673)	0.7616 (0.3412)
	SM	7	0.44603 (0.5905)	0.6215 (0.3753)
	SM + G	2	0.13291 (0.13007)	0.2257 (0.1448)
	SM + G	3	-0.00833 (0.15522)	0.006778 (0.1963)
	SM + G	4	0.0869 (0.1188)	-0.06491 (0.2206)
	SM + G	5	0.23004 (0.23413)	-0.01412 (0.2965)
	SM + G	6	-0.45 (0.46281)	-0.3941 (0.301)
	SM + G	7	0.04422 (0.34661)	0.08534 (0.3242)

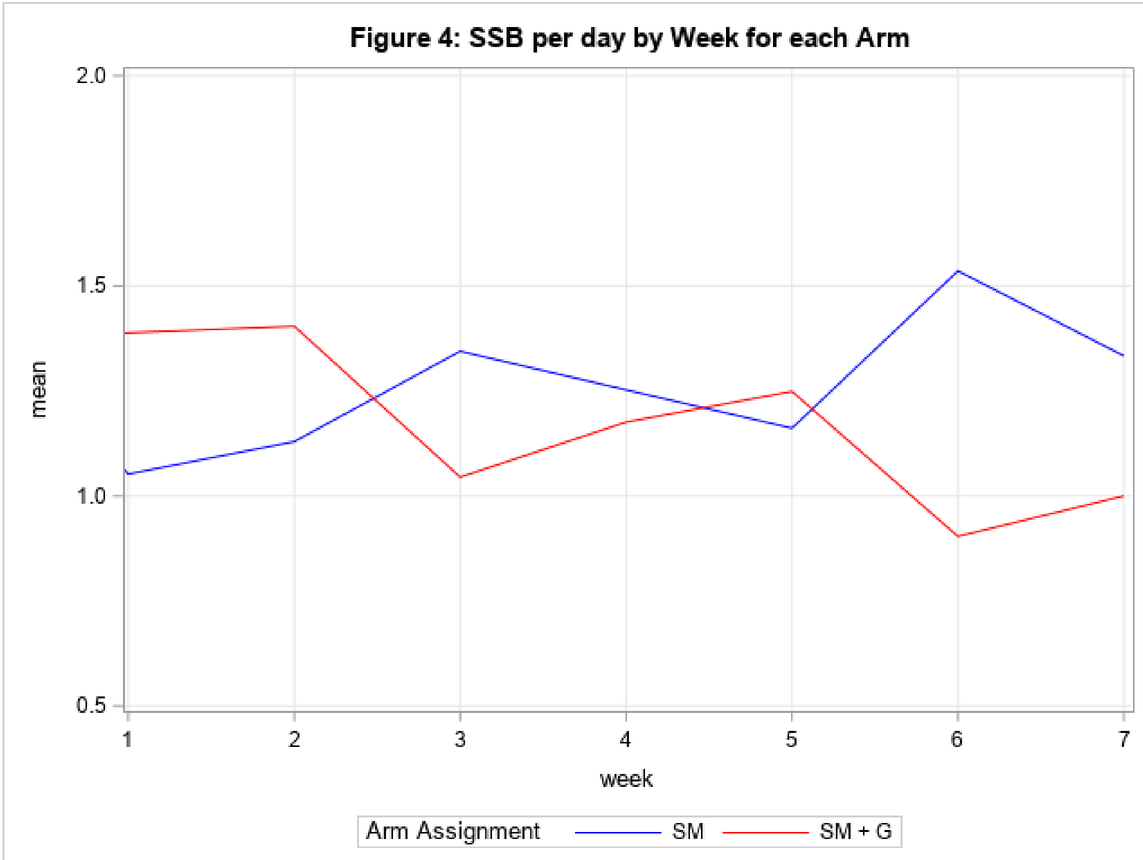


Figure 4: SSB per day by Week for each Arm
2.0
1.5
1.0
0.5
mean
1
2
3
4
5
6
7
week
Arm Assignment
SM
SM + G

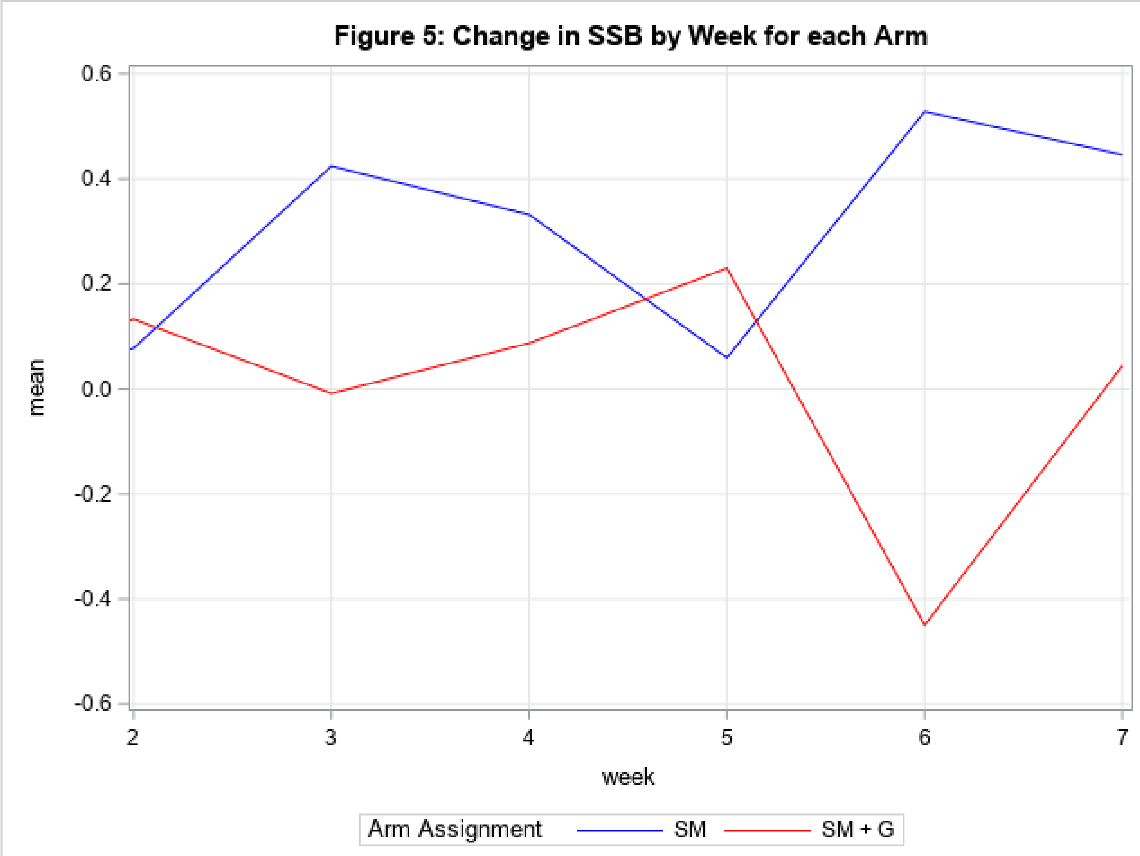


Figure 5: Change in SSB by Week for each Arm
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
mean
2
3
4
5
6
7
week
Arm Assignment
SM
SM + G

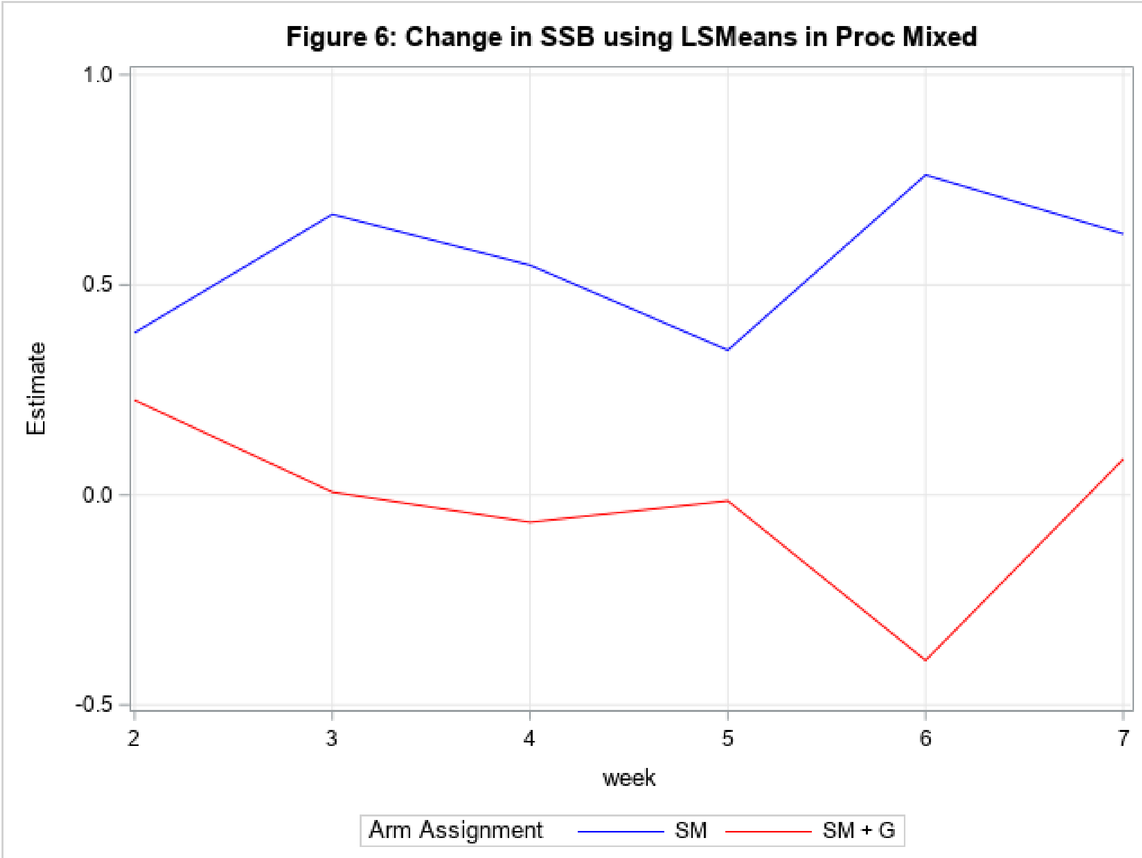


Figure 6: Change in SSB using LSMeans in Proc Mixed
1.0
0.5
0.0
-0.5
Estimate
2
3
4
5
6
7
week
Arm Assignment
SM
SM + G

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