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Imperfect information on physical activity and caloric intake☆

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ABSTRACT

Using the National Health and Nutrition Examination Survey Data, I find that individuals who overestimate their activity level by one standard deviation consume 40–60 extra calories per day, or enough to gain five pounds per year. These extra calories are composed mainly of sugar and carbohydrate, and are concentrated among individuals in the 75th and 90th percentiles of caloric intake. The link between overeating and inaccurate estimation of physical activity is strongest among less educated individuals and individuals with high variance in their physical activity, suggesting that imperfect recall or information gaps explain at least part of the relationship of interest. These results imply the existence of a necessary condition for physical activity-based information treatments to be effective in changing health behaviors and obesity rates.

1. Introduction

The societal costs of obesity are well documented. Reuters reports that obesity costs $216 billion per year, a figure in excess of the costs attributable to smoking (Begley, 2012). Obesity leads to onset of chronic illness and increased medical care costs (Finkelstein et al., 2003; Flegal et al., 2010). Overweight and obesity may lead to lower earnings, lower productivity in the workplace (Cawley, 2004; Baum and Ruhm, 2009; Gregory and Ruhm, 2009) and less favorable outcomes in the marriage market (Oreffice and Quintana-Domeque, 2010; Chiappori et al., 2012). Economists and policy makers continue investigate the policy options to address obesity, focusing primarily on information and incentives.

Biologically, body weight is a function of net caloric consumption. If one assumes that individuals have complete and accurate information about their caloric intake and expenditure, body weight is an economic function of the relative costs (time and money) of caloric intake and expenditure. There is considerable debate about the causes of increased obesity rates, as they coincide with several other changes that have affected the relative costs of caloric intake and expenditure: an increase in the availability of convenient unhealthy food, changes in the economic environment and relative food prices, escalating portion sizes, decreased smoking, technological advances in sedentary entertainment, and shifts towards sedentary employment (Cutler et al., 2003; Powell, 2009; Chou et al., 2004; Courtemanche, 2009; Courtemanche et al., 2015b; Lakdawalla and Philipson, 2009; Lakdawalla et al., 2005; Sarma et al., 2014). Prior work has shown that education and personality traits impact health behaviors and obesity (Webbink et al., 2010; Cutler and Lleras-Muney, 2010; Conti and Hansman, 2013). More recent work has

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incorporated hyperbolic discounting, and a very present-focused "dual self" that makes choices inconsistent with expected present discounted value maximization (Courtemanche et al., 2015a; Scharff, 2009; Ikeda et al., 2010). Ruhm (2012) also points out that food producers have become more effective at targeting present-valuing impulses. Regardless of the determinants, if individuals have full information, are making rational decisions and becoming obese as a consequence, incentives will be necessary to change health behaviors.

Alternatively, if individuals are operating under incomplete or inaccurate information about their net caloric intake, then it is possible that improved information may affect individuals' health behaviors, increase the effectiveness of incentive programs, and improve welfare. From a policy perspective, information goods can be less costly to produce and implement than incentives for individuals. However, evidence on whether individuals respond to generalized health information on caloric content (or smoking) is mixed and somewhat idiosyncratic to setting (Downs et al., 2009; Elbel et al., 2009, 2013; Khwaja et al., 2009; Schwartz et al., 2012). Emerging work has shown that information interventions must be highly personalized to affect changes in health behaviors (Darden, 2015).

Previous mixed responses to information raises the question of whether individuals have accurate information or beliefs about their caloric expenditure (and consequently caloric needs). If individuals' beliefs are inaccurate, are these inaccuracies linked to eating behaviors? Most prior work that has assessed individuals' awareness has found that individuals are aware of what constitutes a 'reasonable daily caloric intake,' or are aware of their caloric needs within a 500 calorie range (Schwartz et al., 2012). While most of the previously cited field work has utilized general and somewhat coarse information, (e.g., labeling food as "healthy," caloric content posting, or invitations to eat smaller portions), small information imperfections in caloric needs or intake can lead to considerable changes in body weight over time if not corrected. For example, consuming 50 calories in excess of one's daily requirement can increase body weight by 5 pounds per year.[1]

This paper demonstrates that individuals perceive their physical activity levels with error, and this error is linked to caloric intake. I use nationally representative data, the 2003–2004 and 2005–2006 National Health and Nutrition Examination Survey (NHANES) data. The NHANES asks about self-reported physical activity, but also contains data on accelerometer-recorded physical activity over seven days. I use the reported and recorded data on physical activity to measure the extent to which individuals over (or under) estimate their physical activity. I show that individuals who overestimate their level of physical activity eat more calories, most of which come from sugar and carbohydrates. According to recent work by Riera-Chrichton and Tefft (2014), calories from carbohydrate lead to expected greater weight gain than fat or protein. Overestimating one's level of physical activity by one standard deviation leads to an increase of 40–60 calories per day, sufficient to cause or 4–6 pounds of weight gain per year.[2] These results show the existence of a necessary condition for information to change behaviors: individuals misunderstand their activity level (and therefore their caloric needs) and this misunderstanding is linked to food consumption decisions.

There are several empirical challenges that must be overcome to claim evidence of a behavioral mechanism, such as imperfect information, from misreporting in survey data. The NHANES is uniquely well suited as it contains data on reported and recorded weight, reported and recorded physical activity, and reported nutritional intake; which enables us to separate the effects of deliberate misreporting. This paper attributes the misreporting of physical activity to either intentional or unintentional misreporting, (acknowledging that some 'intentional' misreporting may happen subconsciously), claiming that that unintentional misreporting of physical activity is driven by imperfect information. Consistent with prior findings of favorable reporting bias in survey data, there is evidence of a systematic relationship between misreported body weight and misreported exercise.[3] Empirically, I mitigate the confounding effects of intentional misreporting by increasingly restricting the estimation samples to individuals who accurately report their body weight.[4] While I cannot positively eliminate all bias from intentional misreporting of exercise, I empirically demonstrate that reducing the bias from intentional misreporting strengthens the main result.

It is also possible that controlling for intentional misreporting as described above, that positive correlation in unintentional misreporting of physical activity and nutritional intake, rather than imperfect information, is responsible for the result of interest. This is unlikely, however, as validation studies of food diary and food recall in the NHANES and other surveys have found that individuals very seldom over-report their food intake (Horner et al., 2002; Archer et al., 2013). Additionally, the empirical results are not consistent with the hypothesis that our results are driven by positive correlation in misreporting of physical activity and caloric intake. If this was the case, one would expect a positive, statistically significant relationship between misreported exercise and

[1] The nutrition field (e.g., Mayo Clinic) holds that a 3500 calories roughly equates to 1 pound of fat, but acknowledges there is considerable heterogeneity among individuals.

[2] Clearly, this is only true so long as information imperfections persist and biological processes are relatively constant. Sooner or later, the bathroom scale or changing clothes sizes should revise individuals' expectations about caloric needs, but I cannot capture those dynamic aspects in cross-sectional data.

[3] However, this paper shows that this type of misreporting will bias these results downward.

[4] This paper acknowledges the substantial literature on joint misreporting on health variables and differential misreporting on the basis of income and education, including D'uva et al. (2008), Butler et al. (1987), Suziedelyte and Johar (2013), Johnston et al. (2009) and Ljungvall et al. (2015). However, the empirical analysis and sample restrictions are motivated by two notions. First, if individuals are accurately reporting their body weight, they are less likely to lie about their physical activity. Second, conditional on intention to accurately report physical activity, what else but imperfect information or mis-perception would cause an individual to mis-report? The results in this paper support both notions.

several nutritional inputs. However, only the estimates for calories, sugar, and carbohydrate are significant. Estimates for protein, fat, vitamin A, calcium, caffeine, and alcohol are insignificant.

I also conduct robustness and falsification tests to alleviate concerns about omitted variable bias from factors such as apathy or level of concern about health. The NHANES contains reported data on other unhealthy behaviors, including consumption of cigarettes, alcohol, and caffeine. Results indicate that overestimation of physical activity is not strongly related to any of these behaviors, nor does including variables for these behaviors in the main regressions significantly affect the main results. Finally, I demonstrate that conditional on recorded exercise, there is no significant relationship between consumption of alcohol, cigarettes, or caffeine and reported exercise. In all cases, these results hold under tighter sample restrictions on the basis of accuracy in reporting body weight, as a proxy for overall accurate reporting.

In the absence of a valid instrument or policy change, I cannot positively eliminate omitted variable bias from correlation in unintentional misreporting or other latent factors. However, Oster (2014) and Altonji et al. (2005) have defined a bounding procedure by which we can understand how strong selection (or omitted variable bias) must be to falsely generate a given result. Using these procedures, I estimate the necessary strength of selection on unobservables, relative to selection on observables, to falsely generate our results. Implementing these same techniques, I can bound the estimated 'true' effect of misperceived physical activity on nutritional intake. Results using Oster bounds imply that the main results are most likely not attributable to selection on unobservables or omitted variable bias.

In short, this paper finds that misreported exercise is strongly related to intake of sugar, carbohydrates, and total calories; and that this result strengthens as the sample is strategically restricted to isolate the effects of unintentional misreporting. While I cannot rule out self-serving bias as an explanation, the effect of unintentional misreporting (which is interpreted as stemming from imperfect information) is most pronounced among those who have high variance in their physical activity levels and those who have not been to college. Individuals with higher variance in their daily activity will likely estimate their "typical" physical activity behavior with greater error (Bordalo et al., 2013). Similarly, individuals with less education are more likely to exhibit information gaps.[5] Most of these marginal calories from overestimated physical activity are comprised of sugar and carbohydrate. A quantile regression specification finds these results are largest in magnitude and significance among less active individuals and individuals in the 75th and 90th percentiles of caloric intake. I check that these results are robust to the inclusion of reported variables strongly correlated with attitudes about health. I check that overestimated exercise appears to affect only food intake, not any of the aforementioned unhealthy behaviors. Similarly, consumption of cigarettes, alcohol, caffeine and sodium do not significantly inform the misreporting of exercise. All of this evidence is consistent with the notion that individuals have imperfect information about their physical activity (and by extension, their caloric requirements) and these information imperfections are related to their food intake. Results are also most pronounced among men.

It should be re-emphasized that these estimates are to be interpreted descriptively, rather than causally. These results cannot be interpreted as a treatment effect of information. Rather, these results provide evidence on the existence of an information gap that is highly policy relevant. In a world with well labeled food, if individuals accurately perceive their caloric expenditure, or if the misperception of caloric expenditure is unrelated to food intake, any information intervention is unlikely to be effective. Changing eating behaviors will almost certainly require more expensive incentive schemes. However, these results highlight the potential for physical activity-based information treatments to change behaviors, if sufficiently precise.

2. Data

Data for this study are taken from the Centers for Disease Control's National Health and Nutrition Examination Survey. The NHANES is a repeated cross-section that contains information on physical health, mental health, body weight, and health behaviors. Nearly all waves contain data from respondent interviews and a subsequent physical examination. For only the 2003–2004 and 2005–2006 waves, respondents were fitted with a waist-mounted accelerometer, which recorded individuals' level of physical activity each minute of the day. As the activity monitor was not used in subsequent waves, only the 2003–2004 and 2005–2006 waves of the NHANES are used in this analysis. The NHANES data contain measured and reported body weight, recorded and reported physical activity, and a recall of all things respondents ate or drank in the last 24 h.

2.1. Timing of data collection process and implications for reverse causality and simultaneity bias

The timing of the data collection mitigates the effects of 'priming', e.g., respondents overestimating their physical activity because they are embarrassed about their recorded weight. Data were collected from the respondents in the following order:

1. Respondents were asked about body weight, various physical activity habits, and other health topics.
2. Respondents participated in a physical exam in which they were weighed, measured, and asked to recall everything they had to eat or drink during the last 24 h.
3. Respondents were fitted with an activity monitor to track their movements over the next seven days. They

[5] A working paper by Cawley and Choi (2015) also shows that there is heterogeneity in overall misreporting between individuals of varying education and other observable characteristics. I rely on sample restriction by accuracy in reported body weight to mitigate deliberate misreporting.

were provided an envelope to return the monitor at the end of that period.
4. At some point in the first ten days after the physical exam, respondents were again asked to recall what they had to eat or drink during the last 24 h.

The timing of the collection of these variables makes reverse causality (greater food intake causes overestimation of physical activity) virtually impossible. Respondents were asked about their physical activity habits in an earlier session than they were asked about their nutritional intake. If the timing was reversed, it would be plausible that reported caloric intake could cause overestimation of physical activity as respondents sought to ex post justify their eating behaviors. The timing of the collection implies that high reported caloric intake cannot cause overestimation of physical activity. It is therefore unlikely that reverse-causality drives the result of interest.

The timing of the data collection also reduces the likelihood that these results are driven by simultaneity bias. A type of simultaneity bias is possible if actual physical activity as recorded by the accelerometer is "primed" by the interview and examination. However, this priming effect should lead individuals who report eating a lot to increase their activity, artificially reducing the difference between reported and recorded physical activity. This would cause the main result to understate the true effect.

2.2. Variable construction and summary statistics

Table 1 contains the combined summary statistics from the estimation sample taken from the 2003–2004 and 2005–2006 waves of the NHANES. Individuals were asked about their height and body weight and subsequently measured. I include controls for measured height, income, age, education and race in each regression.[6] Subscapular skinfold is a measure of the individual's body fat composition.

For reported nutrition, individuals were asked to recall everything they ate or drank in the last 24 h. Individuals were shown containers and approximate measures for serving sizes. From these individually reported items, NHANES calculated composite nutritional intakes: total calories, grams of carbohydrate, protein, fat, etc., and various vitamins and minerals. Summary statistics for total calories and (milli)grams of specific nutrients used as dependent variables are in Table 1.

Two challenges must be addressed in measuring the difference between actual and reported physical activity: data for both actual and reported physical activity must each be compressed into a single measure; and comparisons must be made between the two different scales. Regarding the first challenge, I first form an index of reported physical activity by converting frequency responses into amounts of daily physical activity and general activity level. The third panel of Table 1 contains the physical activity variables used to calculate the index, with the summary statistics of the weighted index at the bottom. For the walking/biking and housework variables, individuals were asked if they did those things for at least 30 min in the past month. Respondents then answered questions about how many times and what frequency (day/week/month) they walked or biked (or performed housework). Respondents who reported more than 120 walking or biking sessions per month were topcoded at 120 sessions per month. Duration per session was topcoded at 180 min. Individuals were also asked similar questions about number and frequency of strength building activities and about their general level of activity on a 5 point scale. All values were converted to average daily hours of activity and were weighted by activity-specific metabolic equivalent weights (METs) provided by CDC.[7] I formed the "daily met" values as follows:

- A day is defined as 24 h. Individuals were allocated one MET per hour of reported sleep.
- Reported frequency and duration of physical activities (walking, biking, housework, strength training) were converted from 'times per week/month' and 'duration each time' to 'average hours doing "x" per day'.
- These average hours per day were MET-weighted based on NHANES guidelines (4.0 METs for walking, 4.5 for housework, 4.0 for strength training, 7 for vigorous exercising).
- Hours spent watching TV per day were allocated as one met per hour.
- Hours not spent watching TV, sleeping, or doing specific physical activities were weighted using self-reported "typical daily activity" (1.4 METs per hour for 'light walking' to 1.8 METs per hour for consistently carrying heavy things).
- The twenty-four MET weighted 'typical' MET weighted hours were summed up to form a reported daily MET value.

The primary concern about this index is incompleteness. Obviously, some individuals undertake physical activities that are not included in the NHANES questionnaire. In this case, the difference between reported and actual physical activity will be understated. Empirically, this will lead to a downward bias in the main results. If this uncaptured physical activity among some individuals leads individuals to consume additional food, this will result in a *negative* correlation in overreported exercise and nutritional intake. This will cause the main results to be understated, rather than overstated.

Second, I compress the minute-by-minute activity data reported by the accelerometer (activity monitor) worn by the respondent to daily averages.[8] As the week progresses, individuals spend more time being completely sedentary. The percentage of time that the accelerometer records no movement increases from 62.9% to 73.6%. Conditional on

[6] Controlling for body weight is a double-edged sword. On one hand, larger people do eat more. On the other, body weight is an endogenous variable. I have verified that our results are robust to the inclusion/exclusion of body weight and an happy to share them upon request.

[7] METs express the energy cost of physical activity relative to a conventional baseline level.

[8] Online Appendix Table A2 contains information on the distribution of intensity for each recorded minute of movement by day.

Table 1
Summary statistics.

Variable	Mean	Std. Dev.	Min	Max
Demographic variables				
Age	38.69	14.51	18	65
Black	0.24	0.43	0	1
Female	0.538	0.499	0	1
Hispanic	0.26	0.443	0	1
High school degree	0.74	0.44	0	1
Some college	0.45	0.498	0	1
Bachelor's degree	0.18	0.38	0	1
Income (categorical)	7.25	3.01	1	11
Anthropometry				
Body weight, self-reported (lbs)	176.505	45.399	82	600
Body weight, measured (lbs)	178.43	47.04	74.14	816.20
Height (cm), measured	168.21	10.03	139.00	204.10
Body mass index (kg/m^2)	28.60	6.852	14.65	130.21
Subscapular skinfold (cm)	20.201	7.87	4.60	41.90
Reported energy intake				
Energy (kcal)	2296.81	1046.57	0	9353
Protein (g)	86.08	44.27	0	415.90
Carbohydrate (g)	281.59	138.54	0	1425.38
Total sugars (g)	132.40	87.49	0	768.04
Dietary fiber (g)	15.79	9.79	0	91.00
Total fat (g)	86.01	47.29	0	415.02
Self-reported physical activity				
Avg. level of physical activity each day	2.105	0.837	0	4
Vigorous activity over past 30 days	0.365	0.481	0	1
Moderate activity over past 30 days	0.561	0.496	0	1
Muscle strengthening activities	0.296	0.457	0	1
Number of times each past 30 days	3.924	8.527	0	90
Hours walked or biked (last 30 days)	2.914	8.758	0	100
Hours of housework (last 30 days)	6.181	11.138	0	120
Met-weighted index	35.441	4.065	26.53	47.3
Recorded mean intensity physical activity, by day				
Day 1	174.71	122.36	0	1189.25
Day 2	175.01	124.33	0	991.23
Day 3	169.84	127.26	0	1228.51
Day 4	164.36	123.12	0	1069.07
Day 5	158.64	126.00	0	1122.91
Day 6	146.09	122.81	0	1544.62
Day 7	121.82	113.65	0	1375.70

some movement, the mean and median recorded intensity also decline slightly over the course of the recorded week. The daily averages are reported in the last panel of Table 1. The average daily amount of recorded movement declines over the course of the recorded week. There is more than one plausible explanation. First, one might expect an individual who knows his/her activity is being monitored to exhibit a 'priming' effect, initially respond with increased activity levels, gradually returning to normal levels over the course of the monitoring period. Second, as the week progresses, individuals may be less diligent about wearing the monitor at all times.[9] Daily averages are then averaged to form a weekly average amount of intensity-weighted movement. To alleviate concerns that the measure of actual physical activity is biased by priming effects endogenous to reported variables, I calculate the average index of actual physical activity using only the last four days.[10]

The accelerometer returns integer values on a scale of 0–32,767. Most individuals do not approach the max value, as the 99th percentile of recorded intensity is approximately 4000 for each day. For approximately 4% of the recorded minutes, the accelerometer reported errors. These observations were not included when forming the index. One benefit of the large numbers of observations per individual is that the effect of outlier observations (legitimate or erroneous) is mitigated. Each respondent was recorded for approximately 10,000 min over the course of the week. In the event an accelerometer error

[9] Individuals were supposed to remove the monitor under certain conditions, e.g., bathing. The drop in recorded movement over the measurement period varies somewhat by the day of initial recording. Table A1 contains a cross-tabulation of average daily average by day of initial recording and day of monitor wear.

[10] I have verified that the results do not substantively change when all seven days are included in the formation of the index of actual activity, nor do they substantively change when only the first three days are included in forming the index of actual activity.

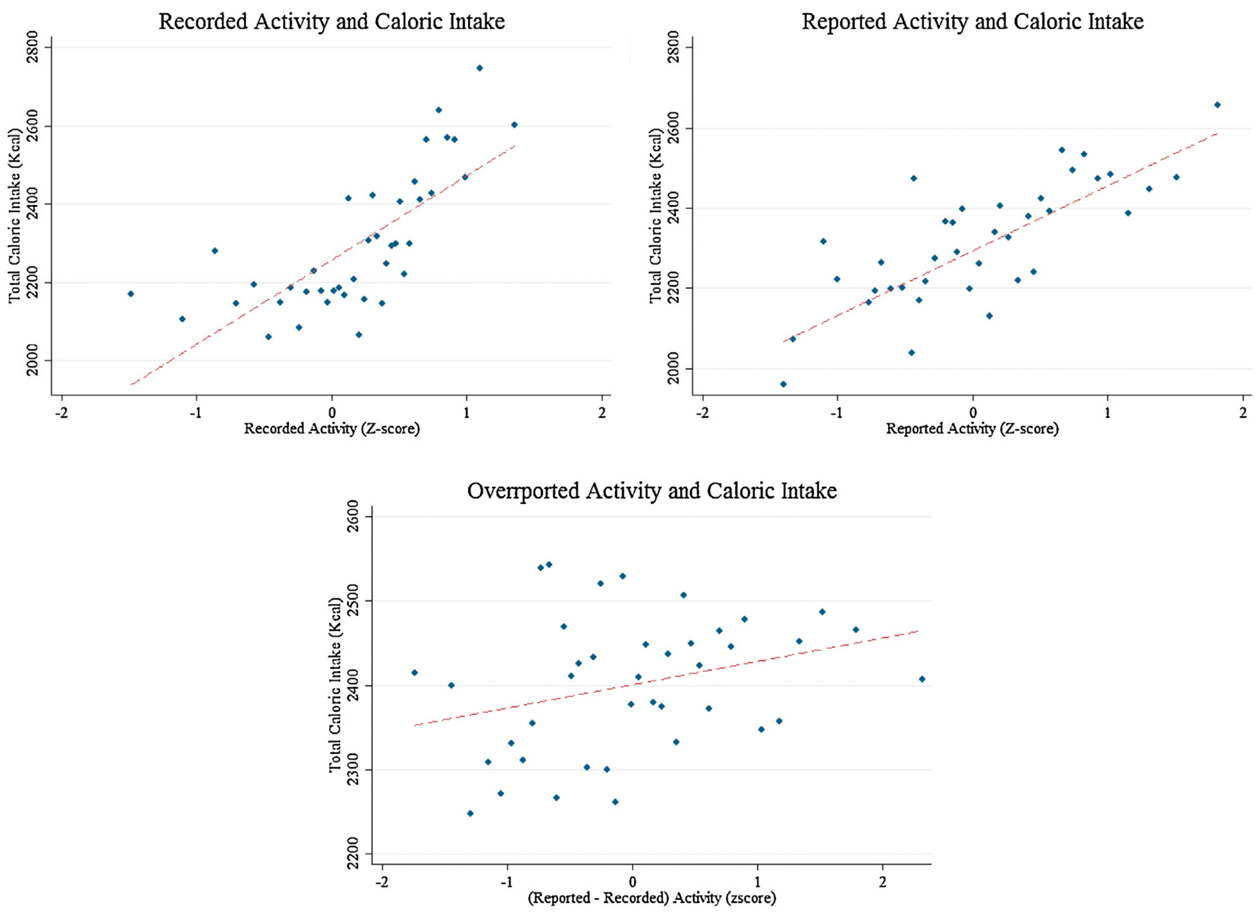

Fig. 1. Mean caloric intake by quantile of recorded, reported, and overreported activity.

was not detected, several false max values (or atypically high true values) would have a relatively small effect on the individual's total weekly average. As the max value was recorded only 121 times in over 69 million recorded minutes, censoring is not a serious concern.

To make comparisons between recorded and reported physical activity, I also must account for the fact that the index of reported and recorded physical activity are on different scales and not directly comparable. To compare the two scales, I calculate the z-score for the individual's reported and recorded physical activity.[11] It should be noted, however that both indexes represent similar values as the reported values from the accelerometer are linear in METs. The difference between the individual's reported and recorded physical activity values is thus the difference in these z-scores.[12] Fig. 1 contains scatter plots of the mean caloric intake for 40 quantiles of the z-scores of recorded physical activity, reported physical activity, and the difference between the two. The cost of combining these scales is that these results can only be interpreted in an ordinal context (i.e., conditional on an average level of actual physical activity, an individual who thinks he engages in above average levels of physical activity will eat more sugar).

3. Empirics

Empirically, this paper investigates the relationship between misreported physical activity and intake of calories or grams of particular ingredients using ordinary least squares regressions. Defining K_i as food intake, A_i^0 for recorded activity, μ_i^A as the difference between reported activity A_i and recorded activity, and $\mathbf{X_i}$ as a vector of exogenous characteristics, the baseline empirical model can be written:

$$K_i = \mathrm{X_i}\beta + A_i^0\gamma_1 + \mu_i^A\gamma_2 + \epsilon_i \quad (1)$$

In order to evaluate whether these associations can be interpreted as causal effects, several confounding factors still must be addressed, including correlated reporting errors for activity and intake, simultaneity or omitted variable bias, and reverse causality.

While Section 2 addressed reverse causality and simultaneity, measurement error and omitted variable bias are

[11] Courtemanche et al. (2015c) show ordinal measures such as percentiles or z-scores are preferable to levels in handling misreported data in the absence of a validation sample.

[12] The empirical distributions of reported and recorded exercise are similar in shape, making z-scores appropriate. I have also conducted this analysis using percentiles of reported and recorded physical activity. The results do not substantively change.

addressed here. Measurement error, classical or non-classical almost surely leads to understatement of the results. Our regression results themselves provide evidence that the key results are biased downward (rather than overstated) by measurement error. While omitted variable bias cannot be eliminated, the results are strongest among individuals for whom information imperfections should be most pronounced. Several falsification tests and robustness checks are also conducted and discussed below.

3.1. Bias from measurement error

Basic econometrics and prior evidence on misreporting indicates that measurement error, classical or otherwise, causes our results to understate the relationship between overestimated physical activity and eating behavior. This claim is empirically supported by repeating each regression with increasingly restricted subsamples determined by accuracy of reported body weight. As the sample is restricted to those individuals who accurately report their body weight, the estimated effect of misperceived physical activity on eating behaviors strengthens.

The NHANES data contain measured and reported body weight, recorded and reported physical activity, and a recall of all things ingested. Denoting K_i for individual's caloric intake, A_i for physical activity/activity, and B_i for the individuals body weight, three variables are measured with error:

$$\begin{aligned} K_i &= K_i^0 + \mu_i^K \\ A_i &= A_i^0 + \mu_i^A \\ B_i &= B_i^0 + \mu_i^B \end{aligned} \tag{2}$$

where for each variable $x \in \{K, A, B\}$, x_i indicates the reported value, x_i^0 indicates the true value, and μ_i^x indicates the reporting error. Unlike most health survey data, μ_i^A and μ_i^B are observed in the NHANES. The only variable in array (2) that is unobserved is μ_i^K, the reporting error for nutritional intake. Ideally, the econometrician would perfectly observe nutritional intake and estimate:

$$K_i^0 = \mathrm{X_i}\beta + A_i^0\gamma_1 + \mu_i^A\gamma_2 + \epsilon_i \tag{3}$$

where $\mathbf{X_i}$ includes height, education, income, and demographic variables. Momentarily abstracting from other sources of bias, γ_2 should be an unbiased estimate of the relationship between mis-perception of physical activity and caloric intake.[13] However, K_i^0 is in not in the data set, only caloric intake measured with error, K_i, is observable. Seeking an unbiased estimate of γ_2, Eq. (3) can be re written as:

$$\begin{aligned} K_i - \mu_i^k &= \mathrm{X_i}\beta + A_i^0\gamma_1 + \mu_i^A\gamma_2 + \epsilon_i \text{ or} \\ K_i &= \mathrm{X_i}\beta + A_i^0\gamma_1 + \mu_i^A\gamma_2 + \underbrace{\mu_i^k + \epsilon_i}_{\nu_i} \end{aligned} \tag{4}$$

where ν_i denotes the new, composite error term in the regression.

Continuing to assume that $E[\mu_i^A\epsilon_i] = 0$, any bias on γ_2 is determined by correlation between μ_i^K and μ_i^A. Evidence from the psychology literature (Crowne and Marlowe, 1960) and economics (Cawley, 2004; Bound et al., 2002) indicates individuals exhibit social desirability bias in surveys, answering questions in ways that will be viewed favorably by others. One would expect ex ante that social desirability bias would lead individuals to understate their body weight, overstate their physical activity, and understate their nutritional intake. If this is the case, $corr(\mu_i^A, \mu_i^K) < 0$ and γ_2 will understate the true effect of misperceived physical activity levels on eating. Cawley (2004) finds evidence of this phenomenon in the NHANES data – that most individuals tend to understate their body weight.

Descriptive evidence from the NHANES data is consistent with social desirability bias. Individuals who understate their body weight also overstate their physical activity, that $corr(\mu_i^A, \mu_i^B) = -0.12$. I compare the average underreporting of body weight for four quartiles of misreported physical activity. Table 2 shows that individuals who overestimate their physical activity the most also under report their body weight by the largest margin. All means are statistically different from one another at the 5% level except the second and third quartiles. The individuals who most strongly over-report their physical activity understate their weight by an average of 2.7 additional pounds relative to those who most strongly under-report their physical activity. If the main results are biased by systematic misreporting, they are biased downward.

I also provide empirical validation that the results of interest are not driven by systematic reporting bias by restricting the sample to those individuals who accurately report their weight to within a certain percent. As the tolerance for misreported weight decreases, the key results strengthen. Thus, the main results are falsely driven by measurement error only if individuals accurately report their weight, but overestimate their physical activity and food intake. This seems unlikely, given the ancillary evidence on the nature of misreporting from previous validation studies on food diary surveys (Horner et al., 2002; Archer et al., 2013).

3.2. Omitted variable bias, correlated unintentional misreporting, and Oster bounds

Omitted variable bias is more difficult to address. If latent personal traits that lead individuals to both overestimate their physical activity and factually eat more

Table 2
Mean misreported weight by quantile of misreported physical activity.

Quartile – μ_i^A	$B_i - B_t^0$
Strong overstatement	−3.16 lbs
Mild overstatement	−2.01 lbs
Mild understatement	−1.67 lbs
Strong understatement	−0.44 lbs

[13] The individual could, of course, be subject to some neurosis/neuroses that compel him to misperceive his physical activity and eat more/less.

(e.g., apathy, self delusion), then $E[\mu_i^A \epsilon_i] > 0$.[14] While this possibility cannot be eliminated, some evidence suggests that omitted variable bias is not entirely responsible for the observed relationship. I split the sample by education levels and by variance in recorded physical activity. While there is no research (to my knowledge) suggesting that individuals' propensity to self-deceive varies by education, it is likely that imperfect recall/information gap explanations will be more pronounced among individuals with less education. Splitting the sample on the basis of variance in activity stems from similar logic. All else held constant, the literature on salience holds that individuals with noisier patterns physical activity will likely estimate their "typical" level of activity with greater error (Bordalo et al., 2013). More pronounced relationships between overreported exercise and caloric intake among individuals with high variance in their activity levels would be consistent with an imperfect information explanation.

The main results are also robust to including misreported weight as a control variable. If these results were driven by self-delusion, incorporating μ_i^B as a control variable (rather than restricting the sample on the basis of μ_i^B) would absorb some of the effect of μ_i^A. Including misreported weight in each regression does not change the results. I also check whether including consumption of cigarettes, alcohol, or caffeine substantially affects relationship between misperceived physical activity and food intake. If the main results are driven by omitted lack of concern about health, including unhealthy behaviors (which should reflect lack of concern about health) would change the results substantially. I also regress consumption of cigarettes, alcohol, and caffeine on the usual set of control variables, including the difference between recorded and reported physical activity. Unlike nutritional intake, misperceived physical activity does not explain consumption of these goods at the extensive or intensive margin. Finally, I regress reported physical activity on recorded physical activity, the usual set of controls, and consumption of unhealthy goods. Conditional on recorded physical activity, results indicate that these other health behaviors have no explanatory power with respect to reported physical activity.

This paper attempts to infer a behavioral mechanism from survey data and takes the position that unintentional misreporting equates to imperfect information. However, while the literature on social desirability bias and deliberate misreporting predicts $corr(\mu_i^A, \mu_i^K) < 0$ in Eq. (4), it is possible that individuals who unintentionally over report physical activity may be likely to over report in others areas such as nutritional intake. This correlation in unintentional misreporting would imply that in the absence of intentional misreporting, $corr(\mu_i^A, \mu_i^K) > 0$, which would create upward bias in our results. The results generally do not support this claim. If some individuals simply overestimate their physical activity and food intake, one would expect them to overestimate their food intake in several dimensions, not just sugar and carbohydrate. As further discussed in the results section, there would have to be a very specific pattern of correlation in misreporting to generate these results.

3.2.1. Oster bounds

Although these results should be interpreted descriptively, regression analysis inherently assumes a causal relationship between the dependent and explanatory variables, including misperceived levels of physical activity on exercise. While evidence from prior validation studies, known patterns in survey response error, and robustness checks from restricted samples supports the notion that information imperfections are at least partly responsible; I cannot definitively eliminate the above alternative explanations for the main result.

Altonji et al. (2005) and Oster (2014) develop a framework to determine the necessary properties of unobservable factors to obtain a given result.[15] Inference is derived from coefficient stability, movement in R^2, and proportionality in selection between observed and unobservable factors. The theory considers a regression model:

$$Y = \beta X + \gamma_1 W_1^0 + W_2 + \epsilon \tag{5}$$

where X is the treatment variable, W_1^0 is a vector of observed variables, and W_2 is a linear combination from unobservable factors and their true coefficients. The frame work assumes orthogonality between W_1 and W_2, as is standard for exogenous control variables. While I defer to Oster (2014) for a full explanation, the main assumptions and implications are as follows. First, there exists some R^2 value, $R_{max} < 1$, that one would achieve if all relevant unobservable factors were included in the model. In the case of nutritional intake, even if we knew the correlation in propensity to misreport (or had personality data), idiosyncratic preferences will still affect food intake. Second, consider a model where nutritional intake is regressed on misperceived physical activity alone. In this case, the probability limit of the estimated coefficient β^0 can be expressed as:

$$\beta^0 \xrightarrow{p} \beta + \gamma_1 \lambda_{W_1^0|X} + \lambda_{W_2|X} \tag{6}$$

where the λ terms represent the population coefficients of regressions of W_1 and W_2 on X. When we include the observable variables, the asymptotic bias becomes:

$$\tilde{\beta} \xrightarrow{p} \beta + +\lambda_{W_2|X} \tag{7}$$

Additionally, the vectors of both observed and unobserved variables can be projected into an index in a linear model. The main implication for this model is that selection on unobservables is proportionally related to selection on observables, or that $\delta(\sigma_{1X}/\sigma 11) = \sigma_{2X}/\sigma_{22}$, where the fractional terms represent least squares regressions of the variable of interest, X, on W_1 and W_2 respectively.

[14] By contrast, social desirability bias implies that $corr(\mu_i^A, \mu_i^K) < 0$, biasing estimates downward.

[15] While both papers frame the issue as 'selection on unobservables', the framework still applies beyond selection, per se (e.g., a latent propensity to over report, or a unmeasurable psychological trait that leads individuals to permanently over report physical activity.)

Table 3
Summary results for Tables A3–A10, estimated effect of overestimating physical activity by one standard deviation on nutritional intake, restricting by percent error in body weight.

Variable	Full sample	$\mu^B/B < 0.15$	$\mu^B/B < 0.10$	$\mu^B/B < 0.5$	$\mu^B/B < 0.01$
Daily caloric intake	26.042	30.748	37.585	41.482	42.424
	(17.375)	(17.501)*	(17.906)**	(19.414)**	(35.610)
Sugar (g)	3.657	4.037	4.341	4.262	5.868
	(1.534)**	(1.548)***	(1.587)***	(1.806)**	(3.180)*
Carbohydrate (g)	5.304	6.077	6.791	6.364	8.197
	(2.359)**	(2.377)**	(2.436)***	(2.725)**	(4.791)*
Protein (g)	0.679	0.759	1.110	0.997	0.518
	(0.742)	(0.746)	(0.768)	(0.857)	(1.527)
Fat (g)	0.696	0.812	1.075	1.100	1.533
	(0.807)	(0.816)	(0.835)	(0.935)	(1.655)
Vitamin A (mcg)	9.240	9.228	12.475	11.156	20.217
	(6.548)	(6.625)	(6.805)*	(7.636)	(14.540)
Beta carotene (mcg)	61.088	40.536	46.356	80.119	170.616
	(53.297)	(54.238)	(56.338)	(67.108)	(144.440)
Calcium (mcg)	10.827	11.488	15.819	16.177	11.371
	(9.216)	(9.373)	(9.559)*	(10.543)	(19.557)
N	5966	5739	5425	4714	1223

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Which combines with R_{max} to yield to expressions. First, the 'true' $\beta^* \xrightarrow{p} \beta$ can be expressed as:

$$\beta^* = \tilde{\beta} - \delta[\beta^0 - \tilde{\beta}]\frac{R_{\max} - \tilde{R}}{\tilde{R} - R^0} \tag{8}$$

In other words, if we assume that selection on unobservable and observable factors are in direct proportion ($\delta = 1$), then we can infer the true beta. Additionally, the above expression can be re-arranged to provide a different insight: For a given $\tilde{\beta}$ and a supposed R_{max}, there exists a single value of δ that implies $\beta^* = 0$: $\delta \approx \frac{(\tilde{\beta} - \beta^*)(\tilde{R} - R^0)}{(\beta^0 - \tilde{\beta})(R_{\max} - \tilde{R})}$.

To implement the bounding procedure, Oster (2014) suggests two alternatives: (a) calculate the bias-adjusted effect with $\delta = 1$ and $R_{\max} = 2 * \tilde{R}$, or (b) calculate δ such that $\beta = 0$. Following Altonji et al. (2005), in most applications, a value of $\delta > 1$ is considered highly unlikely. Finally, while these bounds cannot eliminate the possibility that a given result is driven by unobservable correlated confounding factors, they do provide guidance on the appropriate level of concern for that possibility.

4. Results

Results show strong associations between misperceived physical activity and nutritional intake. In all cases, control variables for demographics, income, education, height, body weight, and actual physical activity are included. First, I estimate caloric intake (or g/mg/mcg of a nutrient, as appropriate). For each regression, I restrict the estimation sample by the absolute percentage reporting error for body weight, μ_i^B/B_i^0, mitigating the bias from erroneous reporting and demonstrating the results are not driven by arbitrary restrictions.

Table 3 contains summary estimates of the effect of overestimating physical activity by one standard deviation on nutritional intake. The only reported results are for overestimated physical activity.[16] For the full sample (column 1), overestimating one's physical activity has a positive and statistically significant association with consumption of sugar and carbohydrates. The downward bias from social desirability in reporting shrinks as the estimation sample is restricted to individuals who accurately report their weight. When the sample is restricted to individuals who accurately report their weight within 15%, 10% and 5%, the estimated associative effect of overestimating physical activity on consumption of total calories, sugar and carbohydrate increases in magnitude and statistical significance. The point estimate is largest when only including individuals who report their weight within 1% error, but the reduced sample size renders the estimates marginally significant at most.

The estimated effect of overestimated physical activity on daily caloric intake in column (4) can be interpreted as "an individual who is at the mean for recorded physical activity, but reports he is in the 84th percentile (1 s.d. above) is expected to consume 41.48 calories per day more than an individual at the mean for recorded physical activity who accurately reports his activity level." The magnitude of this estimate is large. An individual who overestimates his physical activity by one standard deviation is expected to gain 4.3 pounds per year.[17]

[16] See Tables A3–A10 in the appendix for the full results, including other covariates.

[17] The magnitude and significance of this effect is not driven by our use of standard deviation as the unit of measures. Under the same specification, but using percentiles instead of z-scores, an individual who overestimates his physical activity by one percentile is expected to consume 1.23 additional calories per day than if he accurately assessed his own activity. Extrapolating percentiles to standard deviations, the results are similar in magnitude and significance.

Table 4
Oster bounds for key results in Table 3.

Variable	Output	$\mu^B/B < 0.15$	$\mu^B/B < 0.10$	$\mu^B/B < 0.5$	$\mu^B/B < 0.01$
Daily caloric intake	Original estimate	30.748	37.585	41.482	42.424
	Bias corrected estimate	39.336	52.651	60.731	63.08
	$\delta \to \beta^0 = 0$	−3.561	−2.472	−2.131	−2.029
Sugar (g)	Original estimate	4.037	4.341	4.262	5.868
	Bias corrected estimate	2.849	3.456	3.269	4.475
	$\delta \to \beta^0 = 0$	3.334	4.809	4.219	5.199
Carbohydrate (g)	Original estimate	6.077	6.791	6.364	8.197
	Bias corrected estimate	7.592	8.920	8.046	12.238
	$\delta \to \beta^0 = 0$	−3.951	−3.126	−3.7176	−1.966
N	5966	5739	5425	4714	1223

$^{*}p < 0.1$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

The composition of these extra calories is also of interest. Eating more lean protein and vegetables as a result of imperfect information is less unhealthy than increased sugar intake. The second and third rows show that individuals who overestimate their physical activity eat more sugar and carbohydrate. Combining these estimates with the ones from the first row, approximately 60% (75%) of the additional calories associated with overestimation of physical activity are from sugar (carbohydrate). I also evaluate whether overestimated physical activity is linked to increased vitamins. Rows four through eight in Table 3 show that overestimation of exercise is not linked to statistically significant increases in consumption of protein, fat, vitamin A, Beta carotene, or calcium.

For perspective, compare the magnitudes of these estimates with the estimates of the effect of actual physical activity on caloric intake, sugar, and carbohydrate (see Appendix Tables A3–A10). Actual physical activity should (and does) increase individuals' intake more than perceived activity. For total caloric intake, the magnitudes of the estimates for actual physical activity are approximately four times as large (1% significant) as the estimates on overestimated activity. For grams of sugar (carbohydrate), the magnitude of the estimates for actual physical activity is approximately two (three) times as large as that of overestimation of activity. Tables A6 and A7 show that while actual physical activity leads to increased protein and fat intake, the effect of overestimated physical activity is not significant. While actual physical activity is linked to increased uptake of Vitamin A, Calcium and Beta Carotene (Tables A8–A10), perceived physical activity is not. Perceived physical activity may have some positive benefits as it is linked to increased intake of Vitamin C.

Table 4 contains bias-corrected estimates and estimate values of δ necessary for the true, biased-corrected estimate to be zero. For the top set of results, the first row reproduces the original estimates from Table 3. The second row presents estimates corrected for bias from selection on unobservable factors, where selection on unobservables and selection on observables are assumed to be exactly proportional ($\delta = 1$ and $R_{\max} = 2 * \tilde{R} \approx 0.4$).[18] Such an assumption is that selection *into misreporting* has as much explanatory power for nutritional intake as does height, gender, age, education, and income. In other words, these parameter choices probably give omitted variables excess opportunity to explain away the main result. Results for caloric intake and total carbohydrates indicate that our results are likely biased downward as discussed in Section 3. Results for sugar intake imply that biased corrected estimates are closer to zero than the original results, but that selection on unobservables, even given excessive latitude, does not fully explain the full results.

The third row for each variable in Table 4 contains the estimates of δ such that the original result would be obtained if driven entirely by unobservable factors and $\beta = 0$, and $R_{\max} = 2 * \tilde{R}$. For example, on Daily Caloric Intake, in the sample restricted to individuals reporting their body weight with 5% accuracy, that unobservables must be over twice as important to nutritional intake as observable factors and have the opposite direction of influence. The results on Table 4 for sugar, on the other hand imply that selection on unobservables must influence sugar intake in the same direction as the covariates, but be 3.33–5.20 times as important, depending on the sample restriction. Oster (2014) recommends a heuristic cutoff of $\delta = 1$. Again, while I cannot rule out all omitted variable bias, results from this exercise show the relative importance of unobservable factors necessary to explain away the main results.

Table 5 contains summary estimates of the effect of overestimating physical activity on food intake, with the sample split by education.[19] Columns (1)–(3) contain

[18] The assumption that $R_{\max} = 2 * \tilde{R}$ is more rigorous than recommended in Oster (2014). Oster actually recommends using a Π value of 1.3 rather than 2. In a replication sample of 65 results from *American Economic Review, Journal of Political Economy, Quarterly Journal of Economics, and AEJ: Applied*, only 37 percent of results were robust to assuming $R_{\max} = 2 * \tilde{R}$.

[19] Tables A11–A13 in the appendix contain the full results of these regressions.

Table 5
Summary results for Tables A11–A13, effect of overestimating physical activity by one standard deviation on nutritional intake, by percent error in body weight and education level.

Variable	No college $\mu^B/B < 0.10$	No college $\mu^B/B < 0.05$	No college $\mu^B/B < 0.01$	Some college $\mu^B/B < 0.10$	Some college $\mu^B/B < 0.05$	Some college $\mu^B/B < 0.01$
Daily caloric intake	59.220	63.069	131.508	4.137	−6.523	−38.044
	(26.470)**	(30.948)**	(54.674)**	(23.888)	(24.922)	(46.096)
Sugar (g)	6.096	6.864	14.599	1.442	0.741	−2.771
	(2.241)***	(2.657)***	(4.699)***	(2.282)	(2.452)	(4.249)
Carbohydrate (g)	9.942	10.831	19.742	2.209	0.922	−2.679
	(3.510)***	(4.146)***	(7.134)***	(3.405)	(3.520)	(6.452)
N	2868	2193	580	2557	2167	643

*$p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

results for the subsample that never attended college, columns (4)–(6) contain the subsample who attended college. The coefficients of overestimated physical activity on total caloric intake are significant at the 5% level for the subsample who has never been to college, but accurately reports their weight. The estimated effect of overestimated physical activity on grams of sugar and carbohydrate is significant at the 1% level for individuals who have not attended college.[20] The coefficients of overestimated physical activity are much smaller for the subsample who did attend college, and none are statistically significant. As less educated individuals are likely less able to process and utilize information, this is consistent with the hypothesis that information concerns contribute to the relationship between overestimated physical activity and eating.[21]

Table 6 contains summary estimates of the relationship of interest, with the sample split by variance in physical activity.[22] One possible channel for the relationship between overestimated physical activity and caloric consumption is imperfect recall of recent physical activity. For example, Bordalo et al. (2013) show that when individuals recall prior values of prices or usage of a consumer good, they are more likely to remember and attach greater salience to outlier values than central tendencies. Similarly, if individuals do not incorporate their full recent history of physical activity into characterizing their activity levels, but instead overemphasize maximal values (i.e., the day with the most activity is remembered as "typical"), the relationship between overestimated physical activity and food intake will be most pronounced among individuals with the highest variance in physical activity. To that end, the sample is split into thirds by variance in daily recorded physical activity. Table 6 shows that the effects of overestimated physical activity on caloric intake are concentrated in the "high variance" third of the sample. The coefficient on overestimated physical activity is significant at the 10% level. Overestimated physical activity is shown to have an effect on carbohydrate intake for the high variance group, significant at the 5% level. While the point estimate of overestimated physical activity on sugar is largest and 10% significant in the "high variance" group, it is also significant for the low variance group. These results suggest that imperfect recall plays some role in the observed relationship between overestimated physical activity and increased calorie/sugar/carbohydrate intake.

Table 7 contains summary results from a simultaneous quantile regression at the 10th, 25th, 50th, 75th, and 90th percentile of total caloric intake, grams of sugar, and grams of carbohydrate. Full results are available in Tables A17-A19 in the appendix. Overestimation of physical activity is significantly linked to caloric intake only at the 75th (5% significance) and 90th percentiles (10% significance). Note that the estimated effects of overestimated physical activity at the 75th and 90th percentile are roughly five times the magnitude of the estimated effect at the median.

Table 6
Summary results for Tables A14–A16, effect of overestimating physical activity by one standard deviation on nutritional intake, by variance in exercise.

Variable	Low variance $\mu^B/B < 0.10$	Middle variance $\mu^B/B < 0.10$	High variance $\mu^B/B < 0.10$
Total caloric intake	20.503	18.205	68.032
	(28.323)	(30.364)	(34.819)*
Sugar (g)	4.505	2.056	5.549
	(2.417)*	(2.603)	(3.254)*
Carbohydrate (g)	4.565	4.882	10.485
	(3.798)	(4.111)	(4.796)**
N	1807	1813	1805

* $p < 0.1$.
** $p < 0.05$.
***$p < 0.01$.

[20] The unreported coefficients from the non-college subsample not restricted by percentage weight error of overestimated physical activity on caloric, sugar, and carbohydrate intake are all significant at the 5% level.
[21] Consistent with the previous section, results were insignificant for the education split-sample when protein and fat were used as the dependent variable.
[22] Tables A14–A16 in the appendix contain the full results.

Table 7
Summary results for Tables A17–A19, quantile estimates of overestimating physical activity by one standard deviation on nutritional intake, weight error less than 10 percent.

Variable	Percentile				
	10th	25th	50th	75th	90th
Daily caloric intake	8.877 (19.62)	12.462 (20.127)	14.92 (21.928)	74.907 (31.514)**	84.636 (43.208)*
Sugar (g)	0.775 (1.792)	2.346 (1.958)	4.423 (1.926)**	4.479 (2.312)*	8.143 (4.114)**
Carbohydrate (g)	5.275 (2.935)*	4.454 (2.453)*	3.864 (2.463)	7.644 (3.852)**	13.695 (5.761)**
N	4714	4714	4714	4714	4714

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
Main results for Calories, sugar, and carbohydrate intake, by gender: effect of overestimating physical activity by one standard deviation on nutritional intake, by percent error in body weight and education level.

Variable	Male $\mu^B/B < 0.10$	Male $\mu^B/B < 0.05$	Male $\mu^B/B < 0.01$	Female $\mu^B/B < 0.10$	Female $\mu^B/B < 0.05$	Female $\mu^B/B < 0.01$
Daily caloric intake	62.257 (29.441)**	60.419 (31.556)*	90.535 (55.158)	4.601 (20.884)	13.192 (23.027)	-8.047 (46.636)
Sugar (g)	4.539 (2.588)*	4.346 (2.778)*	8.071 (5.008)*	3.126 (1.880)*	4.283 (2.061)**	3.513 (4.054)
Carbohydrate (g)	9.880 (4.007)**	9.055 (4.304)**	14.437 (7.472)*	2.547 (2.831)	4.343 (3.114)	1.474 (6.174)
N	2595	2255	568	2830	2459	655

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Additionally, from Table A17, the coefficients of actual physical activity on caloric intake exhibit far less variation over the support of daily calories. An individual at the 10th percentile of caloric intake (1166/day) is expected to consume an additional 141 calories if he increases his physical activity by one standard deviation, compared to an increase of only 166 calories per day by an individual at the 90th percentile (3638/day) of caloric intake. If an individual at the 10th percentile overestimates his physical activity by one standard deviation, he is expected to consume another 9 calories per day, compared to 84 calories per day by the individual at the 90th percentile. The simultaneous quantile regressions of grams of sugar and carbohydrate exhibit similar patterns. The variation of the effect of overestimated physical activity is considerably larger over the distribution of the dependent variable than the variation in the effect of actual physical activity.

I also examine how the relationship between overestimated physical activity and food intake varies by activity level. Table 9 contains estimates of calories, grams of sugar and grams of carbohydrates consumed.[23] The results in the left three columns are conducted on the subsample with 'less than average activity' ($z^A < \bar{z}$) and the three right columns contain results on the more active sample. The effect of overestimating physical activity on food intake is shown to be stronger, in magnitude and significance, on the less active half of the sample. This is consistent with the notion that individuals who think they are active (but are factually inactive) eat more than those who are aware of their inactivity. These results also serve as a robustness check that the key results are not driven by noisy reports by individuals with high levels of food intake and physical activity.

Finally, to evaluate how the results vary by demographic group, I split the sample by gender (see Table 8). Nearly all of the estimated effects of overestimated physical activity are concentrated among men. However, estimated magnitudes and significance for sugar intake are similar between males and females.

4.1. Robustness and falsification checks

Tables A21–A23 repeat the regressions that produced the calorie, sugar, and carbohydrate results from Table 3, for individuals who report their weight within 10%, 5% and

[23] Full results are in Table A20 in the appendix.

Table 9
Results by activity level.

Variable	Calories $z^A < z$	Sugar $z^A < z$	Carbohydrate $z^A < z$	Calories $z^A \geq z$	Sugar $z^A \geq z$	Carbohydrate $z^A \geq z$
Overreported physical activity (Z-score)	44.679 (25.741)*	4.850 (2.264)**	7.542 (3.524)**	29.052 (25.072)	3.487 (2.242)	5.642 (3.395)*
N	2419	2419	2419	3006	3006	3006

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

1%, but include controls for cigarette, alcohol, sodium, and caffeine consumption. The results do not significantly change when including these variables. As falsification tests, Tables A24–A27 evaluates whether misperception of physical activity has any explanatory power for these non-food-related health behaviors. Regressions for each falsification behavior are run for individuals who report their weight within 10%, 5% and 1% of the true value, both to provide a falsification for each relevant estimation sample, and to demonstrate how results change as the accuracy of reports improve. None of the results for any of these falsification behaviors under any sample restriction were statistically significant. Finally, Table A28 evaluates whether smoking, drinking, caffeine or sodium have any explanatory power for reported exercise. With the exception of smoking in the sample where body weight error is allowed to be up to 10% incorrect, no individual estimates are statistically significant. No individual estimates are statistically significant for the samples where body weight is reported within 5% or 1% accuracy. The health behaviors are not jointly significant in any specification.

5. Discussion

Overestimation of physical activity is associated with higher caloric intake, controlling for demographics, education, actual physical activity, and the size of the individual. The majority of these additional calories are comprised of carbohydrate and sugar, and contain relatively little vitamins and nutrients. These results point to the existence of a necessary condition for activity-based information treatments to be effective: individuals misperceive their activity levels, and that misperception is linked to consumption of more sugar and carbohydrates. These effects are concentrated among less educated individuals and individuals with noisier patterns of physical activity, suggesting that information gaps, at least contribute to the variation of interest. These effects are strongest among less active individuals and individuals in the upper portion of the distribution of caloric intake. In short, our results indicate that the variation of interest is most pronounced among those individuals who would stand to benefit the most from changing health behaviors. This result is consistent with the work of Deb and Vargas (2016), who find that calorie labeling has insignificant effects on BMI at the conditional mean, but when allowing for heterogeneous treatment effects, calorie labeling has positive effects for obese men and overweight women. In short, our results suggest that there is potential for physical activity-based information treatments to change health behaviors, if sufficiently precise and personalized. Experimenting with such high-frequency, precise treatments is an area for future work.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ehb.2017.02.004.

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