To Tell or Not to Tell:

How Observation Impacts Consumption Behavior in Food Choice Experiments

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Selected paper prepared for presentation at the Agricultural & Applied Economics Association's Annual Meeting, Boston, Massachusetts, July 31 – August 2, 2016

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Introduction

Behavioral economics as a branch of economics relies heavily on data from experiments to explain consumers' behavior (Camerer *et al.* 2005; Just *et al.* 2007; Just & Wansink 2009). Researchers usually rely on experiments to discover a relationship between variables of interest given their high degree of internal validity (Roe & Just 2009). Participants generally enter the study, and one of the researchers explains the choices available and the consequences of these choices prior to data collection. Depending on the initial set up, participants may respond differently given what information is available to them, as well as what they perceive the consequences to be. Several economic experiments have documented that participants actions depend heavily on whether they believe experimenters or other participants can observe their behavior (Yamagishi & Cook 1993; Hertwig & Ortmann 2001). The purpose of this study is to identify the impact such observability impacts in a food choice experiment. Food choice experiments have become widespread as a way to inform food policies addressing obesity, marketing, and food safety, among many other topics. We hypothesize that participants' choice of how much to consume in a simple food choice experiment will be heavily influenced by their awareness of if and how consumption will be measured. We also hypothesize that revealing any information to participants will most likely decrease their food consumption during the study.

To understand consumers respond to subtle changes in the choice environment, behavioral economists depend on experiments more than any other branches of economics. With high percentages of obesity prevalence (Lakdawalla *et al.* 2005; Rao *et al.* 2013; OECD 2014), greater emphasis has been placed on the food consumption decisions. The number of behavioral economic experiments examining food consumption behavior has increased dramatically since about 2005. Figure 1 displays the number of hits from a series of Google Scholar searches limited by year published for the terms “food choice” and “experimental economics”. Often times, this research involves the manipulation of various environmental variables in order to determine their impact on food consumption (Van Ittersum & Wansink 2012; van Kleef *et al.* 2012). Given the relatively recent rise of economic experiments involving food choice, little work has been done to determine a set of best practices or how idiosyncratic elements of an experiment may undermine validity.

Food choice experiments are commonly executed both in field settings and in laboratory settings. For example, Just and Wansink (2011) and List and Samak (2015) both make use of field settings (restaurants and kid’s cafes respectively). Alternatively, Lusk and Schroeder (2004) and Messer et al. (2011) provide prominent examples of food choice experiments in a laboratory. Laboratory experiments give researchers more freedom and flexibility to control the settings and to manipulate the interventions (Pirog & Roberts 2007; Wansink *et al.* 2013; Just & Wansink 2014). Given the greater level of control and more direct randomization, laboratory experiments generally have a greater degree of internal validity, and provide a relatively stronger argument for establishing causality (Roe & Just 2009). Field experiments are less flexible, but provide much more realistic choices and contexts, and thus provide results that are more likely to resemble the size and importance of effects one would expect in general application (Roe and Just 2009).

Given the type of food choice experiment, researchers often face the dilemma of what and how much information to give participants regarding the purpose of the experiment, or the types of measures they are collecting. The universe of food choice experiments runs the gamut from experiments where participants are entirely uninformed about what measures are being collected (Hanks *et al.* 2013; Gabrielyan *et al.* 2016), to those where a cover-story is given (Just *et al.* 2009) to those in which all information about measurement and purpose is given (Schulze & Wansink 2012). In this paper, we seek to understand how food choice results vary when participants are aware of the observability of their choices. The results will help to establish sets of best practices in both collecting and interpreting food choice experiment data for the purposes of policy analysis.

Literature Review

Experimental demand characteristics are believed to impact participants' behavior (Durgin *et al.* 2009; Philbeck & Witt 2015). Researchers argue that participants' behavior changes if research hypothesis are (un)intentionally revealed to them (Orne 1959; Durgin *et al.* 2009). Consequently, participants are assumed to act favorably towards completion of assumed hypothesis as a result of social pressure (Orne 1962; Durgin *et al.* 2009). For example, Bhalla and Proffitt (1999) and Proffit (2006) found that participants tended to overestimate slopes and distances if they wore heavy backpacks because of added physical burden. Durgin et al. (2009), however, argued that participants' behavior would change not because of physical but rather social demands of experimental context. The purpose of their study was to identify how participant behavior changed (slope estimates) if they were aware of the main hypothesis of the study. Durgin et al. (2009) divided participants into three groups; no backpack, backpack without information, and backpack with information. The authors found that participant response was affected by the knowledge of the researchers' intentions.

Researchers also argue that participants are eager to please the experimenters which is one of the reasons that the observability impacts the results. That notion is more relevant when studies involve student-participants. More and more experimental studies involve students as participants with or without monetary compensation (Ortmann & Colander 1997; Nichols & Maner 2008). Some researchers argue that financial incentives alone can improve participants' performance during a study (Hertwig & Ortmann 2001). Dictator games are often used in experimental economics to identify how the manipulation of social norms impacts participants' behaviors (Kahneman *et al.* 1986). Hoffman, McCabe and Smith (1996) used dictator games to identify the impact that experimenters have on participants and on their subsequent behavior. The authors found that the experimenter's presence altered the results. Hoffman, McCabe and Smith (1996) argued that participants' actions were not based on their own self-interest but they were rather impacted by the absence of one's anonymity. Burnham (2003) further explored the impact of anonymity on participant's behavior by simply showing pictures of other participants to *dictators*. The author found that the presence of pictures significantly increased the money transfers in the study.

Similarly, many factors impact individual's daily food choices. Social norms, body types of individuals making the food choice and people around them are also argued to have a significant impact on food choices (McFerran *et al.* 2010; Döring & Wansink 2015). Vermeir and Verbeke (2006) argue that individual food consumption behavior and attitude can be changed in the presence of social peer pressure.Since social norms have a significant impact on food consumption on consumers' everyday lives, we would expect observability to be a significant factor during experiments as well. This research examines the presence and the magnitude of an information bias in participants' behavior during food choice experiments.

Data and Methodology

To identify how information about observability impacts participants' behavior during experimental studies, 77 healthy adult individuals were recruited to participate in the study. Participants were assigned to groups of 7 participants each. Each group was assigned to a condition regarding what information was provided at the beginning of each session. Data on food consumption were collected at the Food and Brand Lab at Cornell University which is equipped with several inconspicuous cameras. The study was approved by the university's Internal Review Board. The panelists were recruited and informed they would be watching a television program and consuming food. Participants were provided with the minimum amount of information at the recruiting phase of the study. The recruitment message revealed that a lunch would be provided. Besides a free lunch no other awards or compensation were provided. During a session participants were shown an episode from Bing Bang Theory TV show (season 3, episode 22). After each session, participants were given a short survey including socio-demographic information.

The sessions were organized at the same time for each session (12-1:30 p.m.) and included a lunch of pasta, mixed vegetables, a bread stick and water. The amount consumed was the variable of interest. The food was weighed before and after each session to provide an accurate measure of total consumption. The treatments varied the information that panelists received immediately before the television show started. The information consisted of two fluctuating variables, video recording and weighing, that we provided in different combinations. Control groups were not told that we would be weighing the food they consumed. Treatment groups were either told that we would be videotaping their session to determine their consumption (VIDEO), that we would be weighing their food to determine their consumption

(WEIGH), or that we would be both videotaping and weighing their food to determine their consumption (BOTH).

While there are validated measures of consumption that can be generated from video of eating, such video would not be available for those in the WEIGH condition. Thus, in order to compare consistent measures across treatments, in each case we used the physical weight of food before and after consumption to determine actual amount consumed. The comparison is made using ordinary least squares, simple difference in means t-tests. All analysis was conducted using STATA (version 14.1).

Results and Discussions

Overall, 77 individuals participated in the study. However, due to a few missing survey responses and one low turnout session, the final number of observations used in the analysis is 70. Summary statistics (including each treatment group data) are presented in Table 1. Participants, on average, consumed 347g of their food. We had more female (64%) than male (36%) participants with an average age of 28 years. The majority of participants were Caucasians (59%) followed by Asians (26%) and those of other races (15%). While 36% of those participating had a bachelor's degree, 29% had some college or an associate's degree. High school graduates (18%) and those with advanced or professional degrees (18%) were also relatively well represented in the sample. The income variable was divided into low (0 – $39,999), medium ($40,000 – $99,999) and high ($100,000 or more) income branches with 19%, 47%, and 34% respectively falling in each group.

Results of the experiment are reported in Tables 2 and 3. To check if there was any significant difference in consumption between treatment groups we run unpaired t-tests (Table

2). Mean consumption levels and standard deviations are also reported in the table. The consumption was 310g, 369g, 307g and 390g in in CONTROL, WEIGH, VIDEO, and in BOTH, respectively.

We notice that there is no significant difference between CONTROL and VIDEO respectively. However there is a significant difference between CONTROL and WEIGH and CONTROL and BOTH, respectively. T-test results show that the consumption in BOTH was significantly higher ($p<0.05$) compared to consumptions in CONTROL and VIDEO. Similarly, the consumption in WEIGH was significantly higher ($p<0.10$) compared to consumption in VIDEO ($p<0.10$).

Results of OLS analysis are presented in Table 3. Treatments are included as dummy. Revealing the weighing information before a session has a positive and a significant ($p<0.05$) impact on the amount of food participants eat during a session. Participants consumed 88g more food if told that their food is going to be weighed after the study. Recording information, on the other hand, did not have any significant impact on food consumption. Men, on average, consumed 59g more food compared to their female counterparts ($P<0.10$). Those who report snacking on chips at least once a week, on average, consumed 58g more during the study ($P<0.10$).

Discussion

The current study captures the impact of participants' knowledge of food consumption measurement on food choice behavior in an experimental setting. The findings show that participants' behavior changes significantly depending on the information they receive before the study. At first glance, the results seem counterintuitive. While we might normally expect that individuals would feel self-conscious and reduce their consumption when being watched, telling participants that we are going to weigh their food to determine how much they ate appears to lead to *greater* consumption. When we consider the context of our experiment, our results may make more sense. We have to remember that participants come to experiments knowing that researchers are running some type of study. If we do not tell them anything it may be that they are more cautious about what researchers are looking at. When we reveal that our primary purpose is to weigh their consumption it may lead them to be less reluctant and they behave more natural. Notably, most food choice experiments would fall into a similar context in which participants may be searching for some sort of idea of what is being measured. Alternatively, we could also tell the story that when participants know that we are weighing their food, they decide to eat more than they would naturally in order to comply with what they believe the experimenter wants—commonly referred to as a demand effect (Nichols & Maner 2008; Zizzo 2010). If we were to believe this explanation, we would expect the CONTROL results would be a more accurate measure of normal behavior. In either case, it is clear that the degree to which consumers believe they are being watched or measured impacts their food choice decisions and could thus undermine the external validity of the results.

This study underscores the danger inherent in using controlled experiments to examine food choice policy options. Most experimental studies consist of multiple treatments including a control. For example, given the clamor for policies addressing obesity many experimental economists may try to identify the impact of various information or nutrition signals on participants' choices and consumption behavior. The impact is measured by comparing participants' behavior between control and treatment groups. We argue that if the information given to the treatment group varies from control group in some way that provides a clue as to the aim of the experimenter, we do not capture the real change between groups due to the treatment. As our results show, giving participants any information about how their consumption will be recorded increases their consumption. Therefore, the difference between control and treatment groups might be altered by signaling the variable of interest regardless of what that variable is. If the difference between groups is captured using changes in external cues only then differences in panelists' behavior can potentially be fully attributed to these changes. For this reason, it is prudent that if any treatment will be given information that might give them some clue as to how their food consumption will be measured, that clear statements of what will be measured should be given to all groups.

Conclusions

The results suggest that the information provided to participants about the observability of their behavior impacts their consumption behavior during the study. The results, however, were quite different from what we had initially hypothesized. Telling participants that we were going to measure their food consumption actually had a positive and a significant impact on their consumption. On the other hand, the information about the recording did not have any significant impact on panelist' behavior in terms of consumption.

Seemingly counterintuitive, these results provide insights on panelists' behavior during experimental studies and a word of caution to food choice researchers. Knowledge of the researcher's intentions to measure waste is difficult to hide in many food choice experiments—especially if treatments provide some specific normative information about diet. Therefore, depending on the type of the experiment, telling participants what the dependent variable of interest is (food consumption), while keeping the intervention intentions (independent variables including the controls) hidden is most likely to lead to internally valid results.

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Table 1. Definitions and Summary Statistics of Variables

Variable name	Definition	Description	Freq. (%)				
			CONTROL	WEIGH	VIDEO	BOTH	TOTAL
Gender	A dummy variable that identifies participants' gender	0 if female	55.56	61.90	73.33	68.42	**64.38**
		1 if male	44.44	38.10	26.67	31.58	**35.62**
Age	A dummy variable that identifies participants' age	0 if otherwise	50.00	33.33	46.67	42.11	**42.47**
		1 if 23 years or older	50.00	66.67	53.33	57.89	**57.53**
Low Income	A dummy variable that identifies the number of panelists whose annual income is lower than $39,999	0 if otherwise	94.12	78.95	73.33	78.95	**81.43**
		1 if 0-$39,999 annual income	5.88	21.05	26.67	21.05	**18.57**
Medium Income	A dummy variable that identifies the number of panelists whose annual income is between $40,000 - $99,999	0 if otherwise	35.29	73.68	73.33	31.58	**52.86**
		1 if $40,000-$99,999 annual income	64.71	26.32	26.67	68.42	**47.14**
High Income	A dummy variable that identifies the number of panelists whose annual income is more than $100,000	0 if otherwise	70.59	47.37	53.33	89.47	**65.71**
		1 if more than $100,000 annual income	29.41	52.63	46.67	10.53	**34.29**
Race	A categorical variable that identifies panelists' race	1 if African American	0.00	14.29	0.00	5.26	**5.48**
		2 if Asian	22.22	23.81	26.67	31.85	**26.03**

		3 if Caucasian	66.67	57.14	60.00	52.63	**58.90**
		4 if Hispanic	5.56	0.00	13.33	5.26	**5.48**
		5 if Other	5.56	4.76	0.00	5.26	**4.11**
Education	A categorical variable that identifies panelists' level of education	1 if high school graduate	16.67	14.29	26.67	15.79	**17.81**
		2 if some college or associate degree	22.22	33.33	26.67	31.58	**28.77**
		3 if Bachelor's degree	44.44	33.33	33.33	31.58	**35.62**
		4 if Advanced or professional degree	16.67	19.05	13.33	21.05	**17.81**
Weekly snacking	A dummy variable that identifies the frequency of panelists' snacking on chips	0 if otherwise	66.67	80.95	53.33	63.16	**67.12**
		1 if panelists eat chips at least once a week	33.33	19.05	46.67	36.84	**32.88**

Table 2: Consumption Differences between Treatment Groups: Results of t-test Statistics

Treatment groups		CONTROL	WEIGH	VIDEO	BOTH	***Consumption (in grams)***
		p-values of two-tailed tests*				*Mean (Std. Err.)*
CONTROL	**p-values of one-tailed tests****		0.143	0.974	0.064	*310.056 (158.753)*
WEIGH		0.071		0.123	0.422	*368.714 (77.989)*
VIDEO		0.482	0.062		0.040	*307.200 (137.872)*
BOTH		0.032	0.211	0.020		*389.738 (85.880)*

* - Alternative hypothesis – Group means are not equal to each other
** - Alternative hypothesis – One group means is greater than the other

Table 3. Characteristics That Impact Panelists' Consumption During an Experiment

	Coefficient	Std. Err.
Weighing	88.45**	45.05
Recording	8.14	52.41
Weighing*Recording	-8.86	63.24
Gender	59.02*	33.15
Age_22	-8.46	39.94
Higher Education	-8.18	35.15
Medium Income	8.88	39.31
High Income	-8.05	44.37
Weekly Snacking	58.06*	33.57
Constant	265.94***	50.53

*   - significant at 10% level
** - significant at 5% level
***- significant at 1% level

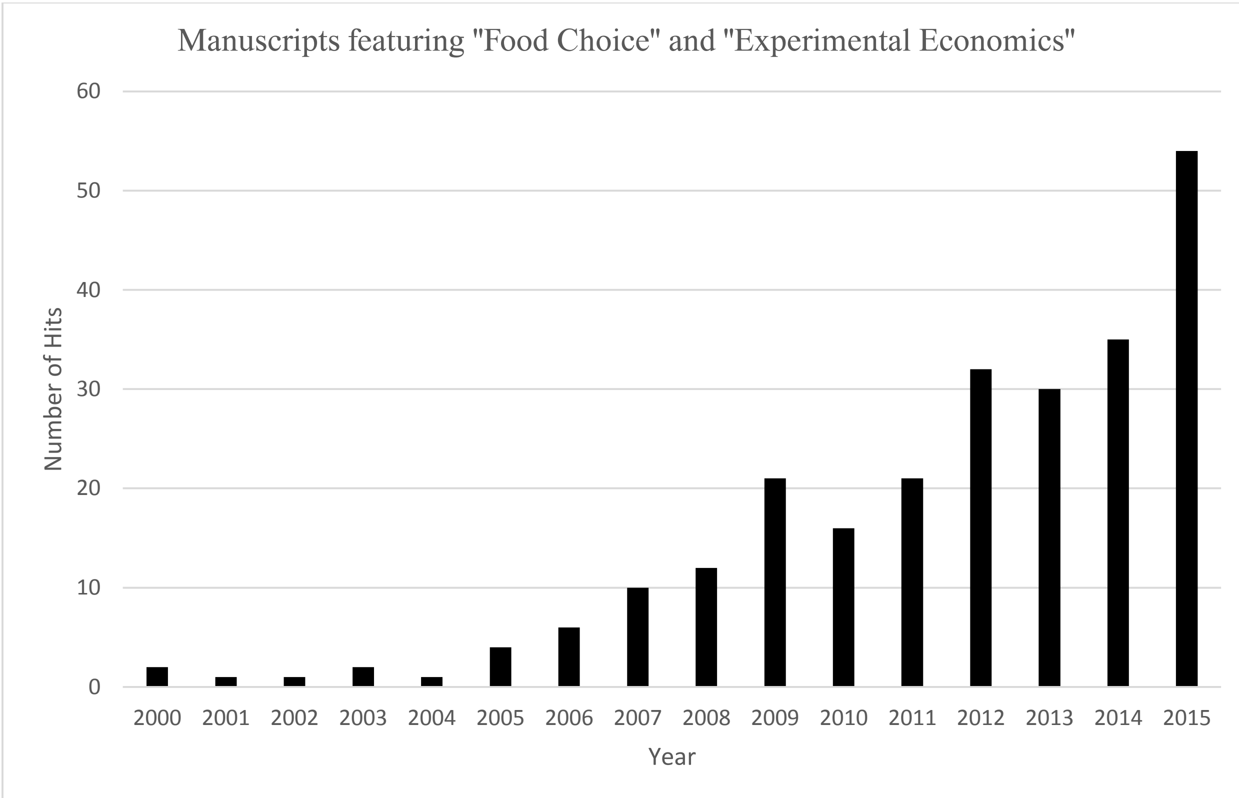

Figure 1. Google Scholar results by year for search terms “Food Choice” and “Experimental Economics”.