Food planning and obesity*

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Abstract

The share of obese individuals in the US has reached an alarming level. In 2016, one out of three was classified as obese. The emerging dominance of large supermarket chains with extensive product selections and targeted selling strategies has played an indispensable role. The aim of this paper is therefore to elaborate on the relationship between food planning, measured by the frequency of shopping list use and assumed to alleviate impulsive buying, and obesity. At question is whether individuals from different socioeconomic backgrounds are equally affected. The paper finds for a representative US sample of 15,661 individuals that members from households with household income below the poverty guidelines ("Poor") who *never* shop with a grocery list are 11.5% more likely to be obese as compared to poor individuals who *almost always* shop with a list. No relationship between food planning and obesity is found for individuals from low- or high-income households. However, the paper argues that food planning should be incentivised regardless of socioeconomic status. Through food planning, poor households should be rewarded with a bonus that is additional to financial assistance in food acquisitions and wealthier households should be reminded in times of abundance of the necessity of acquisitions.

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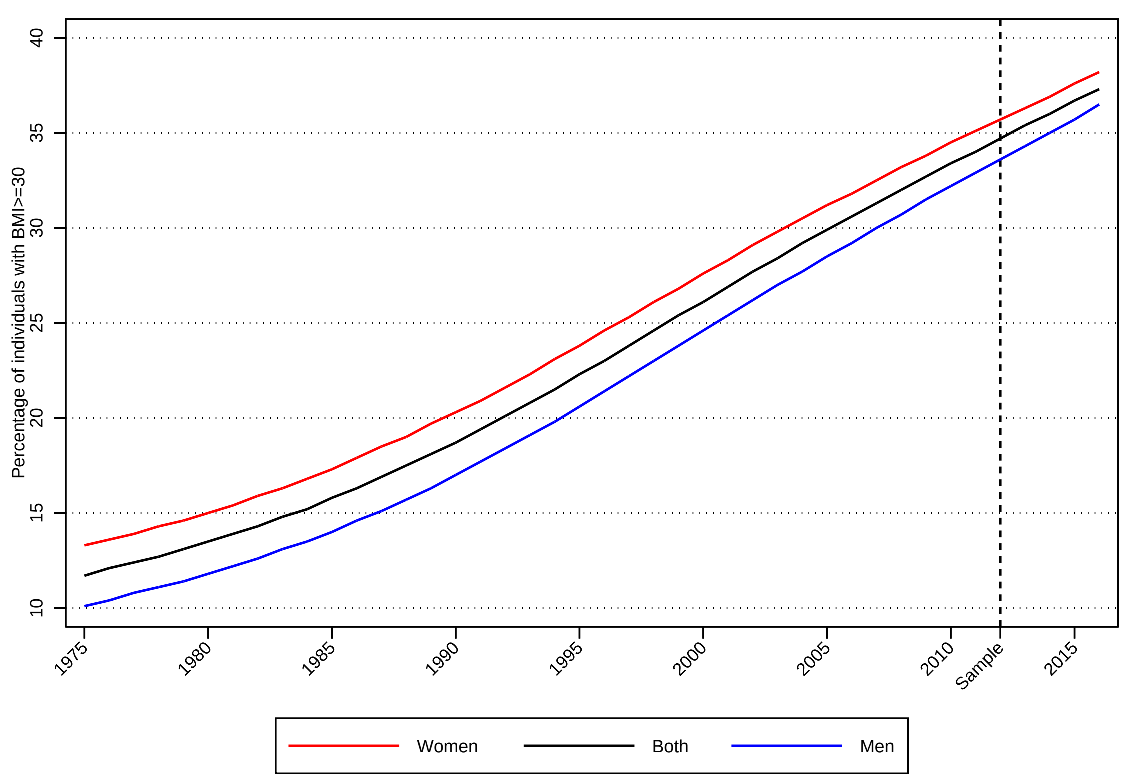
1 Introduction

In 2009/2010, 22.9% of the US population was at high risk for the Metabolic Syndrome, a constellation of five clinical risk factors for cardiovascular disease.[1] While three of these risk factors (blood pressure, HDL-C and triglycerides) decreased since 1999/2000, abdominal obesity and insulin resistance increased. Especially the increase in obesity is alarming. The share of obese US people with a Body Mass Index (BMI) of 30 or more has steadily been rising since data is being collected. Data from the World Health Organization[2] show that 12% of US citizens were classified as obese in 1975. This percentage more than tippled in the subsequent forty-one years and stood at 37% in 2016 (see Figure 1). The leading causes for obesity are manyfold and complex but it is known that obesity increases the risk for cardiovascular disease. Due to the complex nature of obesity, a multitude of theoretical models exist to explain it (c.f. Ulijaszek (2017)). An explanatory approach that has a long history in obesity science depicts the energy balance model.[3] It puts the energy intake and the energy expenditure into relation. Weight gain is the result of increased energy consumption without an equal increase in physical activity. Obesity occurs if such a positive energy environment is maintained for a prolonged period of time.



Note: Data of the crude obesity estimates is from the World Health Organization. The dashed vertical line refers to the sample period.

Figure 1: Prevalence of obesity in the United States of America from 1975 to 2016

1. Hiram Beltrán-Sánchez et al., “Prevalence and Trends of Metabolic Syndrome in the Adult U.S. Population, 1999–2010,” *Journal of the American College of Cardiology* 62, no. 8 (2013).

2. Data available from http://apps.who.int/gho/data/view.main.BMI30Cv?lang=en

3. Stanley J. Ulijaszek, *Models of Obesity: From Ecology to Complexity in Science and Policy*, Cambridge Studies in Biological and Evolutionary Anthropology (Cambridge University Press, 2017).

The devotion to neoliberal market practices since the 1980s and the subsequent globalisation favoured positive energy environments and thus a more rapidly rising obesity share (see Figure 1).[4] This energy imbalance resulted on one side from a decreased energy expenditure that is due to the mounting presence of convenience devices such as motorised vehicles, computers and chairs amongst other things.[5] On the other side, globalisation allowed for global sourcing and empowered transnationally active supermarket chains "[...] which shape eating patterns of populations almost everywhere, supplying energy-dense foods at lower prices than more nutrient-dense foods such as fruit and vegetables."[6]

At present day, supermarkets dominate the end-market of grocery shopping. 95% of US food acquisitions occur in a supermarket or superstore.[7] This dominance of large supermarket chains in today's food supply has exposed individuals to a multitude of food choices. Grocery shopping has thus become a complex interplay between price, taste, nutrition, convenience and assortment.[8] Yet, socioeconomic determinants constrain people's food choices.[9] "There is an argument that individuals select rather than choose freely."[10] In other words, individuals select from the supermarkets' offer given some constraints such as class, gender, income and ethnicity. At the same time, supermarkets aim at maximising the product selection of customers through targeted selling strategies that encourage impulsive buying.

Grocery shopping lists are potential tools to steer through strategic selling environments of targeted energy-dense food sales. A shopping list can function as a memory aid, as a guide to resist impulsive buying and as a planning tool that structures food purchases.[11] A shopping list forces the consumer to think about food purchases before entering the selling environment. It has been shown that particularly among individuals of low socioeconomic status (SES) "[...] lists may be particularly effective at directing purchases if, after paying for all items on the list, there are little or no funds remaining to spend on discretionary items like snack foods and sweets."[12] Table 1 shows that the mean (median) difference between US individuals *never* using a grocery list and people who *almost always* use a grocery list is 3.6 (20) kilocalories per 100g. Purchased calories monotonically decrease with the frequency of shopping list use. According to Table 1, however, using a shopping list more frequently does not reduce total sugar purchases systematically.

4. Ulijaszek, *Models of Obesity: From Ecology to Complexity in Science and Policy*.
5. Ibid.
6. Ibid., p. 7.
7. The data that is used to calculate this number is described in section 2.
8. Tamara Dubowitz et al., "Using a Grocery List Is Associated With a Healthier Diet and Lower BMI Among Very High-Risk Adults," *Journal of Nutrition Education and Behavior* 47, no. 3 (2015).
9. Martin Caraher and John Coveney, "Public health nutrition and food policy," *Public Health Nutrition* 7, no. 5 (2004).
10. Ibid., p. 591.
11. Dubowitz et al., "Using a Grocery List Is Associated With a Healthier Diet and Lower BMI Among Very High-Risk Adults."
12. Ibid., p. 1.

	Means		Medians	
	Energy (kcal)	Total sugar (g)	Energy (kcal)	Total sugar (g)
Shops with grocery list: Never	210.5	10.2	164.0	3.9
Shops with grocery list: Seldom	208.8	9.6	160.0	3.9
Shops with grocery list: Sometimes	207.5	10.0	150.0	4.2
Shops with grocery list: Most of the time	207.5	10.1	149.0	4.2
Shops with grocery list: Almost always	206.9	10.0	144.0	4.0

Notes: Numbers refer to 100g servings. Means (or medians) refer to the average (or midpoint) of the energy or sugar levels of all the purchased items per list use frequency group. The data is explained in section 2.

Table 1: Purchased calories and sugars as a function of shopping list use frequency

The aim of this paper is to elaborate on the relationship between shopping list use frequency, an instrument to plan grocery shopping, and obesity. Considering the energy balance model, and assuming identical energy expenditure levels[13], a higher likelihood of obesity among individuals who *never* use a shopping list is expected as opposed to individuals who *almost always* shop with a grocery list. Particularly of interest is the question whether individuals of different socioeconomic status as measured by household income are equally likely to be subject to obesity given their food planning routines. Especially for individuals of high-income households who are less financially constrained, the relationship between shopping list use and obesity remains to my best knowledge unstudied.

The structure of the paper is the following. The next section describes the dataset and the applied econometric method. Section 3 shows the regression results and section 4 underlines some concluding remarks.

2 Data and Method

The dataset comes from the United States Department of Agriculture's Economic Research Service Unit[14]. It is the outcome of a nationally representative survey of food purchases and acquisitions of American households during April 2012 and January 2013. The survey includes data from 4,826 households of heterogenous socioeconomic status (i.e. supplemental nutrition assistance program (SNAP) households, low-income households not participating in SNAP, and higher income households) as well as individual-specific information for every household member (N = 15,661). Every household member was asked to provided precise information about his/her food purchases during a 7-day time range within the survey period. Along every shopping event, detailed information about the purchased items are provided.[15]

13. This is a strong assumption but inevitable due to the lack of data to control for energy expenditure in the empirical specification in section 2.
14. Data and additional information available from: https://www.ers.usda.gov/data-products/foodaps-national-household-food-acquisition-and-purchase-survey/
15. The dataset reports place of acquisition, nutritional characteristics such as calories, sugars, etc. of the purchased items, etc.

Table 2 shows mean, standard deviation (SD), minimum (Min.) and maximum (Max.) for the sample together with the number of observations (N) for the main variables.

The percentage of obese individuals in the sample is with 35% equivalent to the US population as depicted by the dashed line in Figure 1. The sample features considerable heterogeneity among the explanatory variables. While 19% *never* shop with a grocery list, 10% *seldom* use a list, 22% *sometimes*, 19% *most of the time* and 31% *almost always*. Women are with 53% slightly more present in the sample compared the men. The sample majority is of white ethnicity (70%) and in possession of a high school degree (60%). The sample mean of monthly average household income is 3,910 US$.

	Mean	**SD**	**Min.**	**Max.**	**N**
Dependent variable:					
Obese (BMI >= 30)	0.35	0.48	0.0	1.0	15,661
Explanatory variables:					
Shops with grocery list: Never	0.19	0.39	0.0	1.0	15,661
Shops with grocery list: Seldom	0.10	0.30	0.0	1.0	15,661
Shops with grocery list: Sometimes	0.22	0.42	0.0	1.0	15,661
Shops with grocery list: Most of the time	0.19	0.39	0.0	1.0	15,661
Shops with grocery list: Almost always	0.31	0.46	0.0	1.0	15,661
Individual controls:					
Female	0.53	0.50	0.0	1.0	15,661
Smoker	0.24	0.43	0.0	1.0	15,661
Vegetarian	0.03	0.18	0.0	1.0	15,661
Age	46.46	16.48	3.0	85.0	15,661
Ethnicity:					
White	0.70	0.46	0.0	1.0	15,661
Black	0.13	0.34	0.0	1.0	15,661
Asian	0.05	0.23	0.0	1.0	15,661
Other ethnicity	0.11	0.31	0.0	1.0	15,661
Education:					
School, no degree	0.17	0.38	0.0	1.0	15,661
High school degree	0.60	0.49	0.0	1.0	15,661
University degree	0.23	0.42	0.0	1.0	15,661
Household controls:					
Avg. monthly household income (in 1'000 US$)	3.91	3.73	0.0	25.6	15,661
Avg. monthly income per capita (in 1'000 US$)	1.47	1.61	0.0	25.6	15,661
Household size (in persons)	3.24	1.87	1.0	14.0	15,661
Number of vehicles per capita	0.61	0.47	0.0	4.0	15,661

Table 2: Summary statistics

Given the dichotomous dependent and categorical explanatory variables, I fit a binary outcome logistic model:

$$\text{logit}(O_i) = \alpha + \sum_{j=1}^{4} \beta_j \times SWGL_{i,j} + x'_{i,h}\gamma + \sum_{r=1}^{3} \delta_r + \varepsilon_i \tag{1}$$

The advantage of this model is that it models the probability of being obese as a function of the relative frequency of shopping list use since O_i (for *O*besity) is a binary variable that is 1 if individual i's BMI is 30 or more, 0 otherwise. $SWGL_{i,j}$ (*S*hops *W*ith *G*rocery *L*ist) is a categorical variable that is 1 if individual i reports to shop with frequency $j = \{Seldom,\ Sometimes,\ Most\ of\ the\ time,\ Almost\ always\}$ with a grocery shopping list. $Shops\ with\ grocery\ list = Never$ is dropped due to multicollinearity and used as base level, i.e. the estimated coefficients are relative to it. Additionally, the model features a vector of individual i and household h control variables ($x'_{i,h}$)[16] that are likely determining obesity. Since obesity varies greatly among the different US states, three dummies (δ_r) for the four US census regions are included.[17] Additionally, a constant (α) and an error term (ε_i) that captures unexplained factors are considered. A downside of this model is the lack of information about energy expenditure levels due to unavailable information. The inclusion of the number of vehicles per capita and household is intended, although in an incomplete manner, to control for energy expenditure.

Average marginal effects are reported in Table 3. That is, the estimated coefficients show the probability of being obese as compared to the categorical base level if the variables under consideration are binary. Otherwise, they consider an average individual.

Next to full sample regressions, the sample is split into three subsamples:

i) Individuals who are living in a household with household income that is below the poverty guideline reference income ("Poor").

ii) Individuals living in a household with income between 100% and 200% of the reference income ("Low inc.").

iii) Individuals from households with more than 200% of the reference income ("High inc.").

The Department of Health and Human Services (DHHS) determines the poverty guideline reference income that is dependant on the state of residence and the household size. The reference income is updated yearly. The share of obese Individuals from both, poor and low-income households, is 39%. The share of obese individuals from high income households is with 29% lower.

3 Results

Table 3 reports the regression results from equation 1. Columns (1) to (4) are full sample regressions with 15,661 individuals. Column (1) includes only the four explanatory variables

16. Individual level controls are gender, vegetarian, smoker, age and age^2, education and ethnicity. Household level controls are size (in persons), income and the number of vehicles per capita.

17. Stanley Ulijaszek, *Obesity; Chronic disease and diet*, Lecture in Food and Public Health at UNISG, 2019.

and regional dummies. The estimated coefficients show that individuals who shop *seldom* or *sometimes* with a shopping list are not statistically significantly less likely to be obese compared to individuals who *never* use a shopping list. However, individuals who use a list *most of the time* or *almost always* are 6% or respectively 9% less likely to be obese compared to people who *never* use a list. Columns (2) to (4) add individual and household controls. Due to the addition of the control variables, the coefficients of the explanatory variables decrease in magnitude. Column (4) depicts, for the full sample, that people who shop *almost always* with a list are 6% less likely to be obese compared to individuals who *never* use a list. Despite statistical insignificance, it is apparent to see that the likelihood of obesity becomes smaller the more frequently one shops with a list.

The regression results also show that women are not more likely to be obese than men. Being vegetarian and smoker both reduce the likelihood of being obese, the former by 28% while the ladder by 5%. Also, the regressions convey that elderly are more likely subject to obesity but the effect becomes smaller the older people are. The longer a person stays in school, as measured by the degree obtained, the weaker the likelihood of obesity. It needs to be taken into account that the measured coefficients are relative to attending high school without a degree. Table 3 also conveys that black are more likely do be obese than white but white are more likely to be obese than asian. Individuals from a richer household are less likely subject to obesity.

Column (5) reports regression results for the sample of individuals from households with income that is below the poverty guideline reference income. It becomes apparent that poor people shopping with a grocery shopping list are 11.4% less likely to be obese than poor individuals who *never* use a shopping list. Within the individuals from poor households, the richer the household becomes, the higher the likelihood of obesity. For the sample of individuals from low income households in column (6), no statistical relationship between shopping list use and obesity is estimated. Identically, obesity among individuals from high income households in column (7) is not statistically different between frequency of shopping list use.

4 Conclusion

While this paper finds that individuals from poor households who shop *almost always* with a shopping list are 11.4% less likely to be obese in comparison to poor people who *never* use a shopping list, the causal power of the empirical set-up is limited. The cross-sectional data rather depicts correlational patterns between shopping list use frequency and the prevalence

	Dependent variable: Obesity dummy (BMI>=30)						
	Full sample				Poor	Low inc.	High inc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explanatory variables							
Shops with grocery list: Seldom	-0.023	-0.016	-0.005	-0.006	-0.016	-0.020	0.027
	(0.031)	(0.030)	(0.030)	(0.030)	(0.058)	(0.054)	(0.046)
Shops with grocery list: Sometimes	-0.019	-0.010	-0.007	-0.006	-0.003	-0.034	0.004
	(0.026)	(0.025)	(0.025)	(0.025)	(0.047)	(0.043)	(0.038)
Shops with grocery list: Most of the time	-0.063**	-0.046*	-0.039	-0.033	-0.071	0.010	-0.039
	(0.026)	(0.026)	(0.026)	(0.026)	(0.053)	(0.048)	(0.036)
Shops with grocery list: Almost always	-0.090***	-0.074***	-0.065***	-0.060**	-0.114**	-0.060	-0.032
	(0.024)	(0.024)	(0.024)	(0.024)	(0.046)	(0.042)	(0.035)
Individual controls							
Female		0.030*	0.024	0.020	0.085**	0.037	-0.018
		(0.016)	(0.016)	(0.016)	(0.037)	(0.029)	(0.022)
Vegetarian		-0.307***	-0.288***	-0.280***	-0.144	-0.448***	-0.260***
		(0.061)	(0.061)	(0.061)	(0.111)	(0.119)	(0.083)
Smoker		-0.037**	-0.040**	-0.046**	-0.083**	0.021	-0.082***
		(0.019)	(0.019)	(0.019)	(0.036)	(0.034)	(0.029)
Age		0.013***	0.012***	0.013***	0.016***	0.018***	0.008**
		(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.003)
$Age^2/100$		-0.012***	-0.011***	-0.011***	-0.014***	-0.017***	-0.006*
		(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.003)
Education							
High school degree		-0.052**	-0.049**	-0.032	0.016	-0.059	-0.081*
		(0.022)	(0.022)	(0.022)	(0.037)	(0.037)	(0.044)
University degree		-0.193***	-0.168***	-0.132***	-0.050	-0.162***	-0.178***
		(0.026)	(0.026)	(0.027)	(0.063)	(0.051)	(0.046)
Ethnicity							
Black			0.134***	0.129***	0.123***	0.171***	0.134***
			(0.025)	(0.025)	(0.044)	(0.044)	(0.041)
American Indian/Alaska Native			0.155*	0.147*	0.386***	-0.041	0.258**
			(0.089)	(0.087)	(0.139)	(0.131)	(0.117)
Asian			-0.166***	-0.164***	-0.292***	-0.100	-0.127***
			(0.034)	(0.035)	(0.052)	(0.080)	(0.045)
Other ethnicity			0.028	0.024	0.026	0.052	-0.003
			(0.028)	(0.027)	(0.050)	(0.048)	(0.041)
Household controls							
HH size				0.014***	-0.012	0.036**	0.027***
				(0.005)	(0.012)	(0.015)	(0.009)
HH income (in 1'000 US$)				-0.011***	0.079**	-0.066**	-0.011***
				(0.003)	(0.033)	(0.027)	(0.003)
Number of vehicles per capita/10				0.199	-0.040	0.073	0.498**
				(0.186)	(0.425)	(0.360)	(0.251)
Census region dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,661	15,661	15,661	15,661	3,885	4,978	6,798

Notes: Clustered standard errors at household level are in parentheses. The coefficients report average marginal effects. *Shops with grocery list: Never* is dropped due to multicollinearity and is the reference group. Similarly, *School, no degree* and *White* are dropped and are the respective base levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Regression output

of obesity. It is plausible but not clear that the use of a shopping list reduces the likelihood of being obese. For instance, it might be the case that individuals who carefully plan their shopping trips with a list are also attentively screening energy intake and expenditure. The smaller prevalence of obesity among these individuals would result from attentiveness but not from list use in the first place.

Nevertheless, food planning – or thinking about food purchases before entering the selling environment – should be incentivised. Since this paper finds a statistically significantly decreased likelihood of obesity among individuals from poor households who shop *almost always* with a list as compared to poor individuals who *never* use a list, food planning should yield a reward that is additional to financial assistance in food acquisitions (i.e. SNAP).

For wealthier households, food planning could stimulate consciousness or raise awareness in times of abundance and affluence for the necessity of acquisitions and possibly spill over to food unrelated materialistic purchasing decisions (i.e. clothing, electronic devices, etc.).

An incentive scheme that grants credits for acquisitions that are 'planned' and 'meaningful' could be implemented through a smartphone application that is provided by a governmental entity. The application allows to register grocery items that are intended to be purchased before entering a specific selling environment. Entrance to a selling environment is measured through the connection with the environment-specific WiFi network. At the supermarket check-out, items that are registered in the application ('planned') and nutritionally, socially and environmentally qualified ('meaningful') receive credits.[18] These credits can be used to pay for specific purposes, such as educational fees, health insurance payments or tax bills. The credits are designed in such a way that they are not currency substitutes and only reimbursable for specific services (not products). Importantly, the scheme is positively formulated, i.e. reflected actions are rewarded. Impulsive buying is still possible at no direct additional cost.

Such a scheme places greater emphasis on qualitative aspects of acquisitions and will ultimately benefit the acquirer, the community and the planet earth.

Word count: 2,364 words

18. The idea is that food items that are nutritionally rich (i.e. minimal processing, low in added sugar, etc.), socially acceptable (i.e. no child labour, fair contracts, etc.) and with a minimal environmental impact (i.e. seasonal and local, packaging, transportation, etc.) should be promoted.