The Effect of Household Technology on Obesity and Weight Gain among Chinese Adults

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ABSTRACT

Background:

During the past two decades, Chinese society has undergone a major economic transformation, including changes in health-related behaviors and lifestyles. The number of obese people has risen rapidly in China. A portion of the blame has been attributed to the adoption of household technology, such as food-preparation technologies, washing machines, entertainment products, etc. The direct relationship between household technology implementation and weight gain or obesity still lacks conclusive evidence. It is important to learn from China's experience of how household technology growth triggers obesity epidemics in our rapidly developing world. This paper uses the China Health and Nutrition Survey (CHNS), from 1997-2009, to understand the role of household technology adoption and its potential to cause weight gain or. We believe that household technology encourages sedentary lifestyles resulting in less energy expenditure on low intensity activities which triggers weight gain or obesity. We hypothesize that (1) household technology adoption, independent of exercise and daily calorie consumption, is a cause of obesity and weight gain. (2) Household technology has different impacts on weight gain or obesity by gender due to dissimilar lifestyles and technology related behaviors at home

Methods:

Utilize data from 13,037 males and 14,103 females from 12,285 households between the ages of 18 and 55 who participated in the 1997, 2000, 2004, 2006 and 2009 study in the China Health and Nutrition Survey (CHNS). Linear and logistic fixed-effects regression to estimate net effects of adopting household technologies on weight gain and obesity, adjusting for survey year, age, age square, marital status, socioeconomic status, and health-risk behaviors. Full models consist of time-variant mediating variables, including the variations of total daily energy intake, exercise, occupational activity, household activity, and transportation activity. All analyses are stratified by gender.

Results:

The results showed that, for females, adopting washing machines is associated with increasing BMI .11 ±.05 kg/m^2 (*p*<.05*). Possessing food preparation technologies is associated with increasing BMI .24 ±.02 kg/m^2 (*p*<.05*). The ownership of computers is associated with deceasing BMI .18 ±.06 kg/m^2 (*p*<.01**). Each motorized vehicle increases the odds of obesity by 29 % (*p*<.05*). Each food-preparation technology increases the risk of obesity by 17% (*p*<.05*), and computers decreases the chance from non-obesity to obesity (*p*<.10†). For males, household ownership of food-preparation technologies or air conditioners is associated with increasing BMI (.06±.03 kg/m^2, *p*<.05*; .18 ±.07 kg/m^2, *p*<.01**). There is no significant association between household-technology and obesity in males.

Conclusion:

This research addresses how rapid household technology adoption can account for weight gain and obesity. Household technology has a greater impact on female obesity. The study provides the evidence that overall energy intake and exercise may not function as a mediator for the link between household technology ownership and weight gain and obesity. Future public health policy may evaluate interventions focused on increasing low intensity activities impacted by household technologies.

Key words: Obesity; Household-technology; Gender; Fixed-effects; Longitudinal study; China Health and Nutrition Survey (CHNS)

Background

Obesity has been found to be an independent risk factor for many health conditions and is associated with increased hazard ratios for mortality (Adams et al. 2006; Berrington de Gonzalez et al. 2010). The relationship between obesity and the risks of hypertension, coronary heart disease (CHD) and Type two diabetes (T2D) is well-recognized in Chinese populations (Li et al. 2002). China has experienced extraordinary economic and social development, along with an ever-increasing obesity rate, since the last decades of the 20th century (Du, Lu, Zhai, & Popkin, 2002; Ma et al. 2005; Wang, Mi, Shan, Wang, & Ge, 2007). The argument has been made that rapid household technological adoption induces weight growth and the risk of obesity by increasing sedentary lifestyle at home; however, the direct relationship between household technology implementation and weight gain or obesity still lacks conclusive evidence.

A limitation of existing studies on household ownership of domestic technology and Chinese obesity is that they do not adequately capture the dynamic processes of adopting household technology on weight change (Bell, Ge, & Popkin, 2002), nor do they control all the time-invariant confounders, such as unmeasured individual predispositions, which makes it difficult to infer any firm causal judgments (Bell, et al., 2002; Monda, Adair, Zhai, & Popkin, 2008; Qin, Stolk, & Corpeleijn, 2012). Additionally, past research studies in China did not address gender differences with respect to the association of household technology adoption and the risk of obesity (Bell, et al., 2002). Household technologies such as labor-saving devices or food preparation technologies are primarily used to replace the tasks that are completed by women; in addition, evidence has shown that women spend less time with entertainment-oriented products and motorized vehicles compared to men in Western contexts (Sugiyama, Healy, Dunstan, Salmon, & Owen, 2008). In order to understand how obesity is affected by household technology adoption, it is important to take gender differences into account.

There are two main controversial hypotheses to explain the adoption of household technology-obesity link. The first hypothesis is that exercise[1] and total dietary intakes may be said to function as a mediator to the extent that it accounts for the relation between the owning household technology and weight gain. That is, household technology may cut leisure time spent exercising and increase daily calorie consumption, which triggers weight gain or obesity. For example, Jakes et al. (2003) discovered that, for both men and women, increased television viewing greatly decreased participation rates in vigorous activities. Furthermore, TV viewing is positively associated with caloric intake and calories from fat in women; people snack more when they are in front of the TV (Jeffery & French, 1998; French, Story, & Jeffery, 2001). Kobayashi and Kobayashi (2006) observed that the invention of air conditioners brought lifestyle changes to Japan; they suggest that children now spend significantly more time indoors playing video games, watching TV, or studying rather than doing outdoor activities during the hot

[1] Here "exercise" is also referred to as moderate or vigorous activity and leisure-time physical activity, which is "a subset of physical activity that is planned, structured, and repetitive and has as a final or an intermediate objective the improvement or maintenance of physical fitness" (Caspersen, Powell, & Christenson, 1985) . It is different from physical activities at work, home, and commuting.

summer season. However, this hypothesis still lacks direct supporting evidence with large proportions of contradicted results.

An alternative hypothesis is that adopting household technology is an independent factor from exercising and daily calorie consumption for weight gained or obesity. Evidence shows that applying labor-saving devices has resulted in less energy expenditure for women (Lanningham-Foster, Nysse, & Levine, 2003). Substituting TV viewing with loitering around at home is sufficient to expend energy equal to a 6.61 lb (3 kg) weight loss during a year among adults (Buchowski & Sun 1996). Numerous scholars have found the relationship between TV viewing/computer using and obesity remains salient after controlling for exercising and overall food intake (Coakley, Rimm, Colditz, Kawachi, & Willet, 1998; Hu, Li, Colditz, Willet, & Manson, 2003; Koh-Banerjee, et al., 2003; Vandelanotte, Sugiyama, Gardiner, & Owen, 2009). In other words, the decline in low intensity activities may be behind the effect of adopting household technology on the risk of obesity. This decline of low intensity activities, such as chores around the home and hand washing clothes, is relatively independent of discretionary activities that account for the weight gain and obesity.

The empirical evidence shows that the daily calorie consumption has declined while energy expenditure in exercise has increased with an increase in the prevalence of obesity in the past two decades in China (Du, et al., 2004; Ng, Norton, Guilkey, & Popkin, 2012; Ng, Norton, & Popkin, 2009). To explain these diverging trends; we suggest that adopting household technology may play an important role for weight gain and obesity but is independent from daily calorie consumption and energy expenditure in exercise. Household technologies such as labor-saving devices or food preparation technologies are primarily used to replace the tasks that were completed by women; therefore, we suggest that household technology has a greater impact on female weight gain and obesity. Specifically, we are interested in whether ownership of household-technology increases body mass index (BMI) and the risk of obesity among adults ages 18-55 during 1997-2009 in China.

Methods

Study population

The China Health and Nutrition Survey (CHNS) is an ongoing longitudinal project which gathers data on health, nutrition, and socioeconomic indicators at the individual, household, and community levels. The survey began in China in 1989 with follow-ups in 1991, 1993, 1997, 2000, 2004, 2006, and 2009. A multistage, random-cluster process was used to draw an initial sample from 8 provinces. A new province (Heilongjiang) and its sampling units were added in 1997. Counties in each province were stratified by income levels, and multistage random sampling was used to select four counties in each province based on per-capita income reported by the National Bureau of Statistics. Within each county or urban area, neighborhoods were randomly selected from urban and suburban, townships, and villages. Twenty randomly selected households were chosen within each neighborhood. There were 190 primary sampling units including 4,020 households surveyed first in 1989, and all individuals within a household (a total of 15,927 individuals) were interviewed. Follow-up levels were high, but families that migrated from one community to a new one were not followed. Response rates were ~88% at the individual level and ~90% at the household level for participants of the previous year (Popkin, Du, Zhai, & Zhang, 2010).

CHNS data are not nationally representative, as provinces vary substantially in geography, stage of economic development, public resources, and health status. However, previous research findings on key physical composition and dietary data trends based on CHNS are similar to those revealed by nationally representative data (Ge et al. 1994; Wang, Du, Zhai, & Popkin, 2006) Details of the CHNS are described elsewhere (http://www.cpc.unc.edu/projects/china).

For this research, we focus on data where respondents completed the weight and height examinations. Our CHNS longitudinal data subsample includes 13,037 males and 14,103 females from 12,285 households between the ages of 18 and 55 who participated in the 1997, 2000, 2004, 2006 and 2009 study. The study has omitted the 1989-1993 survey due to the year 1989 only collecting information for preschoolers and young adults ages 20-45 and lack of information for physical and transportation activities before 1997. 11.56 % of women were pregnant or breastfeeding and are also omitted.

Measurements

Dependent variable. In this research, body mass index (BMI) is defined as (weight (kg)/ (height (m)^2)) in its continuous form. The dependent variable in the logistic fixed-effects regression models is a binary indicator of obesity. Obesity is coded as 1 if an individual's BMI is greater than or equal to 25 according to World Health Organization's (WHO) pacific region criteria, due to the absolute levels of diabetes and hypertension on the age- and sex-specific basis being higher in people of Asian origin (James, Leach, Kalamara, & Shayeghi, 2012).

Independent variables. CHNS collected information regarding household ownership of electrical appliances and equipment via the following questions: "Does your household own this appliance (yes/no)," and "does your household own this type of transportation (yes/no)?" In this study, we examine the relationship between mean BMI/obesity and seven types of household technologies. We suppose that individuals who live in households that have the greatest ability to adopt all kinds of technologies would have the most significant weight change. Each technological device in our regression models was recorded as a continuous variable: numbers represent number of appliances owned, and 0 represents the household did not own any appliance. Household technologies are categorized into seven types based on the type of functions and the patterns in the primary regression models. They are (1) televisions; (2) computers; (3) labor-saving device includes washing machines; (4) four food-preparation technologies include refrigerators, microwave ovens, electric rice makers, and pressure cookers. (5) Two communication devices include telephones and cell phones. (6) Air conditioners; (7) two motorized vehicles includes cars and motorcycles. Note that CHNS only collected the household ownership of cell phones after 2004.

Covariates/Control variables. The time-varying characteristics in this study include: (1) *Survey year*: 1997, 2000, 2004, 2006, and 2009. (2) *Current age*: recoded as age minus 18 from 0 (18) to 37 (55) and entered as a continuous variable; *age square*: the square of current age representing the non-linear relationship of household technology to BMI and obesity. (3) *Marital status*: recoded as a binary variable, currently married and currently not married (includes single, divorce, widow and separated). (4) *Smoking status*: recoded as a binary variable, currently smokes vs. currently does not smoke. Alcohol consumption across surveys has little variation; we have omitted it from the models. (5*) Socioeconomic status (SES):* there are two SES variables used in this study; "education" recoded as no education, primary education, secondary education, and college or above. "Household income" is built by adding each household's nine potential sources of income: business, farming, fishing, gardening, livestock, non-retirement wages, retirement income, subsidies, and other income. When any component was incomplete, an attempt was made to impute the missing data. Details of the imputation are described elsewhere (http://www.cpc.unc.edu/projects/china/data/datasets/convar). For interpretability, household income has been logged. In such models, the logged case refers to the proportional change in the household income for one BMI increase.

***Mediating variables*.** Arithmetically, an individual gains weight through a positive energy balance, that is, when calories that an individual consumes exceeds calories that he/she expends. It is essential to consider changes in dietary consumption and energy expenditure in exercise as key components in weight change between 1997 and 2009 in China. In our study, (1) *daily energy intake* refers to the energy value (per kilocalories) of all food consumed within 24 hours, averaged over 3 days, calculated using 1991 Chinese Food Composition Table. Detailed descriptions of the dietary survey are presented elsewhere (Zhai, et al., 1996). The researchers also controlled the change of kilocalories in daily fat, carbohydrate, and protein intake, but it was found to not significantly alter the estimates and was excluded in the final models. (2) *Exercise* was recoded as a continuous variable summed up by metabolic equivalent (METs) hours per week of a person who participated in activities including: martial arts, jogging, swimming, dancing, aerobics, sports, and others, during a typical day. Detailed descriptions of the measurements of metabolic equivalent are presented elsewhere (Sallis, et al., 1985; Ng, et al., 2009)

Other energy expenditure in non-exercise physical activities controlled in our models include (3) occupational activity, (4) home activity, and (5) bicycling and walking. "Occupational activity" was originally categorized by interviewers into five levels based on participant job characteristics. We found that very light, light, and moderate categories were not significantly different from each other and heavy and very heavy categories were also not significantly different from each other in our regression models; we categorized it as a dichotomous variable with two levels: light vs. heavy. "Household activity" was recoded as a categorical variable based on time spent hours per day on four household activities including: preparing and cooking food, buying food, washing and ironing clothes, or taking care of children age 6 or younger. This field is missing for approximately 45% of male samples in survey year 2004 and 2006; we developed one category for "missing." For the purpose of precise measurements, we also created a continuous variable summed up by metabolic equivalent (METs) hours per week of a person who participated in any of four home activities and presented in different models at Table 4. "Transportation activity" also contains one-fourth missing values; we recoded it as a categorical variable based on whether or not the participants walked or biked to school/work and "missing." For the purpose of precise measurements, transportation activity was recoded as a continuous variable summed up by METs hours per week in different models at Table 4. Note that the cases are excluded when there is no information of home or transportation activity in Table 4. Detailed descriptions of the measurements of metabolic equivalent are presented elsewhere (Sallis et al. 1985; Ng, et al. 2009)

Statistical analyses

We selected linear/logistic fixed-effects (FE) regression models because it has two attractive features. First, FE models are efficient in estimating the effect of variables that vary considerably within an individual. Second, FE models are designed to study the causes of changes within an individual by controlling for potential unobserved heterogeneity bias, so that we can generalize our results to all of the individuals that have been selected. The Hausman test indicates the unique errors (u_i) are corrected with the regressors in our models (Greene, 2008), which means that fixed effect is preferred over random effects for statistical analyses (*p*<.000***). Specifically, the linear regression model with time-invariant covariates in our study is written as below:

$$y(BMI)_{it} = \alpha_t + \sum_{k=1}^{K} \beta_k \, x_{kit} + \sum_{m=1}^{M} \gamma_m \, z_m + u_i + \varepsilon_{it} \tag{1}$$

Where α_t is an intercept that may be different for each survey year; β and γ are vectors of coefficients. x are time-varying covariates, including one of our independent variables and was recorded as a continuous variable: numbers greater than 0 represents the household owned the number of appliances and 0 represents the household did not own the appliance. It also includes covariates that we have controlled in our study, such as, survey year, age, age square, marital status, smoking, SES, and important mediators, such as, daily energy intake, exercise, occupational activity, home activity, and bicycling and walking to work/school. Z are time-invariant covariates including year-specific and person-specific effects that play a role in weight gain and obesity. Covariates with "person-specific effects" are those which affect individuals in different ways but are constant across time, such as, genetic factors or ethnicity. Covariates with "year-specific effects" are those which affect all individuals in the same way but change over time, such as, food policy or obesity legislation, etc. There are two error terms in this model, ε_{it} represents random variation of each individual at each survey year, and u_i represents the effect of all unobserved variables on BMI that vary across individuals but constant over time (Allison, 2009).

FE methods are able to control for all time-invariant covariates by doing the regression with different scores and does not allow the assessment of time-invariant covariates. (Allison, 2009; Baltagi, 2001; Wooldridge, 2002) When subtracting Time 1 from Time 2, u_i and $\sum_{m=1}^{M} r_m\ z_m$ are removed from the equation, and the final equation is written as

$$\Delta BMI_{it} = \Delta\alpha + \sum_{k=1}^{K} \beta_k\ (x_{1it} - x_{kit-1}) + \varepsilon_{it} \tag{2}$$

where Δ is the first-difference operator. This model is meant to test whether there is a net effect of household technology on weight gain (BMI). Specifically, we are assuming a particular direction of causation, that ownership of household technology affects BMI change and not the reverse. The CHNS is panel data which contains observations over multiple time periods, and FE models are able to incorporate all available measurements from each individual (level 1), which maximizes our analytic sample. In those models, the "cluster" refers to each individual when repeated measurements in each year are nested (level 2).Our FE models also include household level variables including the ownership of each household technology and household socioeconomic status.

We used comparable FE logistic regression models to estimate the odds of obesity when an individual's household did not own an electrical appliance and compared this to the odds of obesity when the same individual's household owned an electrical appliance by "using his own control" (Allison, 2009). Finally, researchers have indicated that household technology may have different impacts on men and women; we ran the models separately by gender. All FE models were run on Stata version 13 (Stata Corporation, College Station, TX, USA).

Results

Percent of homes with each form of household technology, 1997-2009

Table 1 shows the trend from all the households in CHNS possessing each form of technology since 1997. The sample shows that Chinese households have been achieving an impressive rate of household technology transition. Most household technology possession rates increased considerably; over than half of Chinese families possessed at least one washing machine (70.70%), refrigerator (63.66%), rice maker (82.11%), and telephone (57.35%) in 2009. Interestingly, TV set was widely available in China where 96.46% of households owned at least one in 2009, while the possession of a computer (23.94 %), microwave (25.40 %), and particularly car (6%) are still relatively low in 2009.

[TABLE 1 HERE]

The prevalence of obesity/BMI and background characteristics

Table 2 presents our sample on the prevalence of obesity, mean BMI, and individual background characteristics by gender. The researchers found that the average BMI increased from 22.12 kg/m^2 to 23.54 kg/m^2 among males and from 22.47 kg/m^2 to 23.12 kg/m^2 among females during 1997-2009. The prevalence of obesity shares a similar trend; increased from 14.57 % to 30.36 % among males and 18.74 % to 26.49 % among females during 1997-2009.

Reduced exercise and increased diet consumptions have been blamed as the drivers of the obesity epidemic; yet, our sample indicates these trends moved in the opposite direction during 1997-2009. The total energy intake (kcal) decreased while energy expenditure in exercise (METs) increased during 1997-2009. Our selected sample also indicates an increase of hours or energy expenditure in home activities, especially among the male population. Note this field is missing in our sample for 45% of males, so we are unable to make a definite conclusion on this trend. Finally, our selected sample shows that occupational physical levels have shifted considerately from heavy to light and less people bicycle or walk for transportation. Generally, our sample shows that there were substantial changes in lifestyle and behaviors among Chinese adults during the past 12 years.

[TABLE 2 HERE]

The causal effects of the ownership of household technology on an individual's BMI/obesity between 1997 and 2009

FE models are intended to investigate the causes of changes *within a person*. The results of FE regression models examining the causal effects of the ownership of household technology on the mean BMI / log-odds of obesity between 1997 and 2009 by gender are provided in Table 3 and Table 4. Adopting different household technologies could take place at the same year, which may confound the effect of each technology on increasing BMI/ log-odds of obesity; we have included all the technologies in our models. We have controlled the possible time-varying covariates in the basic models including: survey year, age, age square, marital status, socioeconomic status, and current smoking status. The full models control the variations of total daily energy intake, energy expenditure in exercise, occupational activity, home activity, and bicycle or walk for commuting during 1997-2009 in Table 3. Home and transportation activities were recoded as continuous variables summed up by MET hours per week and missing values were excluded in the analysis in Table 4.

BMI. Our models indicate that each food preparation technology increases BMI by .06 ($p<.05$) and an air conditioner increases BMI by .18 in men ($p<.01$; Model 2). In other words, for a man of average height (164.8 cm), adopting a refrigerator, microwave, rice maker and pressure cooker increases his weight by .68 kg, and adopting an air conditioner increases his weight by .49 kg. Women, on the other hand; a washing machine increases her BMI by .11 ($p<.05$), and four food preparation technologies increase her BMI by .20 ($p<.05$); for a woman of average height (154.5 cm), this is equivalent to adding .26 kg and .44 kg respectively (Model 6). Interestingly, our sample also indicates that owning a computer at home decreases female BMI by .18 or .27 kg ($p<.01$).

Obesity. For males, the ownership of household technology is not related to the risk of obesity (Model 3 & 4). For females, there is a significant positive relationship between household ownership of food preparation technologies or motorized vehicles and the likelihood of becoming obese (Model 7 & 8). Each food preparation technology is associated with an odd ratio (OR) of 1.17 ($p<.05$) for becoming obese; motorized vehicles are associated with an OR of 1.29 ($p<.05$).

All the models in Table 3 indicates that the associations between household technology and BMI or obesity remain significant and unchanged after adjusting for the variations of daily energy intake and physical activities; suggesting that the mediating variables do not completely explain this relationship in both men and women.

[TABLE 3 HERE]

Table 4 applies metabolic equivalent measurements to both variables “home activities” and “transportation activities” and excludes the missing cases of both variables. The results show few differences. Overall, both Table 3 and Table 4 show that air conditioners are associated with weight gain in men, and washing machines are associated with weight gain in women. Computers are associated with weight loss in women.

[TABLE 4 HERE]

Discussion

This research investigates whether household technology launched during these past two decades in China has the potential to transform weight-related lifestyles in major ways. The initial household technology adoption took place about five decades ago in Western countries, a time period for which highly accurate, representative data does not exist. In China, however, the initial adoption and spread of household technology has occurred much more recently. Recent empirical data collections in the China Health Nutrition Survey (CHNS) provide an unprecedented opportunity to rigorously evaluate the relationship between initial and rapid household technology adoption and the risk of obesity. It gives excellent opportunity to learn from China's experience of how household technology growth triggers obesity epidemics in our rapidly developing world.

Past studies show that owning washing machines and food preparation technologies is related to a significant increase in weight for men and women (Monda, et al., 2008). Our FE models show that adopting washing machines has no effect on men. Likewise, Bell, et al. (2002) found men in households who adopted motorized vehicles between 1989 and 1997 had greater weight gain. We did not find adopting motorized vehicles to have significant impact on weight gain or obesity in men. These different results may point to past studies being confounded by time-invariant variables which mediate their outcomes.

Our findings indicate that *exercise* and *daily energy consumption* do not function as mediators for the association of household technologies and obesity or weight gain. In fact, our sample shows that the energy expenditure in exercise increased, while daily energy consumptions decreased from 1997-2009. In other words, adopting household technology is an independent factor from exercise and daily calorie consumption for weight gained or obesity. We suggest that access to household technology may reduce low intensity activities, such as chores around the home and hand washing clothes, is the trigger for weight gained or obesity.

The results suggest that household technology may have different impacts on weight gain or obesity by gender due to dissimilar lifestyles and technology related behaviors at home. For example, our data show that washing machines only have impact on weight gain in women but not in men, while air conditioners only have impact on weight gain in men but not in women. This may suggest that washing machines have replaced the low intensity activities at home that were generally completed by women; and air conditioners may encourage men to stay at home rather than doing low intensity activities outdoors. Future research may be directed to investigate gender differences in household technology related health risk behaviors.

The most puzzling finding is that having a computer is associated with a decrease in weight for women. The functions of computers are quite complex compared to the other household devices in our study. For example, watching videos, chatting, or playing online games on computer requires very little mental effort, while writing programs or network management requires greater mental manipulation and involvement from the users. Computer adoption in the Chinese household is relatively new and longer follow-up studies will help to understand the true nature of its impact.

Current public intervention against obesity has focused on promoting education programs that encourage exercise and healthy eating. Our study emphasizes that household technological change may play an important role in weight gain and obesity. A greater understanding is needed of the relative importance of technology adoption and its effect on low intensity activities. For example, food-preparation technologies such as refrigerators may reduce activities such as shopping and chatting at traditional markets daily. Entertainment products and modern conveniences may decrease social behaviors such as walking door to door, playing games in the park, and chatting with neighbors. Entertainment products and communication devices may diminish traveling for communicating with banks, health centers, and libraries or bonding with relatives. Entertainment products may also encourage watching sports, movies, and concerts at home. In short, understanding the mechanisms of household technology that trigger weight gain or obesity has important public health implications. Future public health policy may evaluate interventions focused on increasing low intensity activities impacted by household technologies.

Finally, one of our limitations in this study is that owning a household technology does not mean every individual would use it to its full potential. Unfortunately, there is no information from CHNS about the amount of time or frequency of technology use by each household member. In addition, our analysis does not account for the rapid increase of energy-saving devices in public places, such as elevators, escalators, lifts, automatic doors etc., which are factors that might confound household technology adoption's impact on weight gain and obesity.

Conflict of interest

The authors declare no conflict of interest.

Authors' contributions

CCH conducted the primary writing, designed the study, and analyzed the data. SY contributed to the concept and supervised the study and methods; SY and JK provided critical revision of the manuscript. All authors had final approval of the submitted versions.

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Appendix

TABLE 1

PERCENT OF HOMES WITH EACH HOUSEHOLD TECHNOLOGY BY WAVE (CHNS 1997-2009)

	Year					Change (1997-2009)
	1997	2000	2004	2006	2009	
OBSERVATIONS (Household numbers)	3876	4397	4387	4467	4517	
ENTERTAINMENT PRODUCTS						
Television (%)	50.15	67.73	83.29	89.87	96.46	46.31
Computer (%)	1.81	4.18	8.95	12.60	23.94	22.13
LABOR-SAVING DEVICES						
Washing machine (%)	47.00	52.78	57.37	62.92	70.70	23.70
FOOD-PREPARATION TECHNOLOGIES						
Refrigerator (%)	30.83	38.42	43.21	48.58	63.66	32.83
Microwave (%)	1.81	5.89	15.30	18.85	25.40	23.59
Rice Maker (%)	39.44	48.63	60.22	71.05	82.11	42.67
Pressure cooker (%)	37.08	43.04	43.97	46.95	48.58	11.50
MODERN CONVENIENCES						
Air Conditioner (%)	5.10	8.69	16.58	20.01	27.35	22.25
COMMUNICATION DEVICES						
Telephone (%)	27.77	47.46	66.12	64.02	57.35	29.58
Cell phone (%)[a]	-	-	45.26	57.37	77.30	32.04
MODREN VEHICLES						
Car (%)	2.35	2.81	3.43	3.89	6.13	3.78
Motorcycle (%)	12.41	18.94	25.63	28.20	31.36	18.95

[a] Note that CHNS only collected the household ownership of cell phone after 2004; here the change indicates the change between 2004-2009

TABLE 2
DESCRIPTIVE STATISTICS OF INDIVIUDUAL LEVEL VARIABLES FROM SELECTED WAVES BY GENDER (CHNS 1997-2009)

	Male			Female		
	1997	2009	Change	1997	2009	Change
OBSERVATIONS (INDIVIDUALS)	2492	2665		2599	2903	
DEPENDENT VAR.						
Body mass index (kg/m^2)	22.12	23.45	+1.33	22.47	23.12	+.65
	(2.75)	(3.38)		(2.98)	(3.38)	
Weight (kg)	61.47	66.70	+5.23	54.46	57.35	+2.89
	(9.39)	(11.17)		(8.35)	(9.16)	
Obesity (%)	14.57	30.36	+15.79	18.74	26.49	+7.75
COVARIATES						
Age (years)	37.20	40.67	+3.47	37.87	41.19	+3.32
	(10.24)	(9.87)		(9.80)	(9.61)	
Married (%)	79.65	83.26	+3.61	84.88	89.01	+4.13
Currently smoking (%)	64.77	58.87	-5.90	3.07	2.00	-1.07
Household income (per 1,000 yuan)	15.09	46.60	+31.51	15.14	43.54	+28.4
	(12.60)	(75.58)		(12.46)	(61.67)	
Log household income	9.36	10.20	+.84	9.36	10.17	+.81
	(.75)	(1.45)		(.78)	(1.37)	
Education						
No education (%)	9.63	5.37	-4.26	27.47	15.02	-12.45
Primary education (%)	63.96	60.11	-3.85	52.64	57.18	+4.54
Secondary education (%)	22.87	26.75	+3.88	17.62	21.77	+4.15
College and above (%)	3.53	7.77	+4.24	2.27	6.03	+3.76
MEDIATING VARIABLES						
Daily energy intake (kcal)	2.64	2.46	-.18	2.26	2.05	-.21
	(.71)	(1.36)		(.60)	(.79)	
Exercise (metabolic equivalents, METs)	.04	.05	+.01	.02	.04	+.02
	(.15)	(.19)		(.09)	(.14)	
Home activity (METs)	.08	.11	+.03	.36	.48	+.12
	(.06)	(.22)		(.24)	(.53)	
No activity (%)	52.93	51.18	-1.75	6.89	6.75	-.14
Less than 3 hours (%)	44.22	45.18	+.96	64.41	62.93	-1.48
More than 3 hours (%)	2.37	3.60	+1.23	26.63	29.87	+3.24
Missing (%)	.48	.04	-.44	2.27	.45	-1.82
Bicycle/walk for commuting (METs)	.02	.01	-.01	.02	.01	-.01
	(.03)	(.02)		(.03)	(.03)	
Inactive (%)	10.63	37.00	+26.37	9.20	19.26	+10.06
Bicycle/Walk (%)	73.27	46.08	-27.19	74.53	46.71	-27.82
Missing (%)	16.09	16.92	+.83	16.28	34.03	+17.75
Light occupational activity (%)	48.68	60.41	+11.73	49.17	67.45	+18.28

Only data from 1997 (the baseline) and 2009 (final wave)
Standard errors in parentheses

TABLE 3
FIXED-EFFECTS REGRESSION FOR THE OWNERSHIP OF HOUSEHOLD TECHNOLOGY PREDICTING MEAN BMI/ LOG-ODDS OF OBESITY AMONG MEN AND WOMEN, FROM 1997 TO 2009

	Male					Female			
	BMI			Obesity		BMI		Obesity	
VARIABLES	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HOUSEHOLD TECHNOLOGIES									
TV		.021	.021	.273	.264	.057	.061	.138	.151
		(.059)	(.059)	(.208)	(.209)	(.056)	(.057)	(.175)	(.176)
Computer		.098	.102†	.198	.202	-.177**	-.177**	.017	.007
		(.060)	(.060)	(.179)	(.179)	(.058)	(.058)	(.172)	(.174)
Washing machine		-.033	-.033	.116	.116	.106*	.113*	.042	.065
		(.050)	(.050)	(.163)	(.163)	(.049)	(.049)	(.137)	(.138)
Food technology		.064*	.063*	.058	.058	.055*	.052*	.165*	.158*
		(.025)	(.025)	(.076)	(.076)	(.024)	(.024)	(.073)	(.073)
Communication		.009	.005	.035	.033	.040	.037	-.169	-.182
		(.035)	(.035)	(.111)	(.113)	(.034)	(.034)	(.099)	(.100)
Air conditioner		.171*	.175**	.070	.067	.011	.012	.081	.087
		(.067)	(.067)	(.198)	(.200)	(.064)	(.064)	(.197)	(.199)
Motorized vehicle		.013	-.000	.199	.198	.043	.034	.265*	.252*
		(.042)	(.042)	(.126)	(.128)	(.041)	(.041)	(.118)	(.119)
COVARIATES									
Age	.388***	.392***	.392***	.924**	.931**	.228**	.224**	.182	.196
	(.089)	(.089)	(.089)	(.292)	(.294)	(.083)	(.083)	(.253)	(.257)
Age^2	-.003***	-.003***	-.003***	-.005***	-.005***	-.001***	-.001***	-.001	-.001
	(.000)	(.000)	(.000)	(.001)	(.001)	(.000)	(.000)	(.001)	(.001)
Married	.032	.006	.006	-.004	.014	-.010	-.016	-.406	-.424
	(.078)	(.079)	(.079)	(.265)	(.265)	(.098)	(.097)	(.341)	(.339)
Smoke	-.226***	-.228***	-.227***	-.145	-.140	-.172	-.188	-1.114*	-1.209*
	(.049)	(.049)	(.049)	(.150)	(.151)	(.155)	(.155)	(.520)	(.531)
Education (No education)									
Primary	.058	.057	.060	.473	.501	-.088	-.085	-.109	-.104
	(.105)	(.105)	(.105)	(.413)	(.417)	(.076)	(.076)	(.212)	(.214)
Secondary	.110	.092	.094	.150	.170	-.146	-.147	-.055	-.053
	(.136)	(.136)	(.136)	(.482)	(.487)	(.122)	(.122)	(.325)	(.328)
College and above	.075	.039	.046	-.128	-.126	-.511*	-.513**	.508	.523
	(.184)	(.185)	(.185)	(.671)	(.677)	(.198)	(.198)	(.700)	(.696)
Log household income	.038**	.035*	.032*	.036	.032	.013	.014	-.018	-.018
	(.014)	(.014)	(.014)	(.041)	(.041)	(.014)	(.014)	(.038)	(.039)
MEDIATING VARIABLES									
Dietary intake (per 1,000 kcal)			-.002		-.019		-.008		-.021
			(.017)		(.071)		(.023)		(.070)
Light occupational activity			-.088†		-.159		-.214***		-.384**
			(.052)		(.161)		(.049)		(.144)
Exercise (per 100 metabolic equivalents, METs)			-.024		.143		-.255*		-.603
			(.097)		(.319)		(.124)		(.438)
Home activity									
Less than 3 hours			.078†		.072		.065		-.044
			(.041)		(.136)		(.079)		(.234)
More than 3 hours			.057		.243		.094		.050
			(.106)		(.368)		(.084)		(.250)
Missing			.094†		.023		-.128		-.505
			(.057)		(.175)		(.115)		(.347)
Transportation (Inactive)									
Bicycle/walk			-.062		.165		-.064		.001
			(.046)		(.141)		(.053)		(.173)
Missing			-.097†		.064		-.005		.036
			(.056)		(.170)		(.058)		(.179)
Constant	16.769***	16.676***	16.773***			18.735***	18.900***		
Observations	13,037	13,037	13,037	2,310	2,310	14,103	14,103	2,579	2,579
Number of id	5,975	5975	5975	713	713	6,310	6,310	751	751

Standard errors in parentheses*** p<.001, ** p<.01, * p<.05, † p<.10
All models were adjusted for survey year.

TABLE 4
FIXED-EFFECTS REGRESSION FOR THE OWNERSHIP OF HOUSEHOLD TECHNOLOGY PREDICTING MEAN BMI/ LOG-ODDS OF OBESITY AMONG MEN AND WOMEN, FROM 1997 TO 2009

	Male				Female			
	BMI		Obesity		BMI		Obesity	
VARIABLES	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
HOUSEHOLD TECHNOLOGIES								
TV	-.041	-.041	.505†	.480	-.023	-.034	-.044	-.047
	(.077)	(.077)	(.306)	(.307)	(.064)	(.064)	(.215)	(.217)
Computer	-.009	-.008	-.003	-.022	-.234**	-.234**	-.136	-.160
	(.080)	(.080)	(.237)	(.238)	(.074)	(.073)	(.238)	(.240)
Washing machine	.076	.077	.359	.356	.122*	.127*	.246	.284
	(.069)	(.069)	(.237)	(.239)	(.059)	(.059)	(.190)	(.192)
Food technology	.040	.038	.002	-.006	.032	.026	.167†	.154
	(.034)	(.034)	(.111)	(.112)	(.030)	(.030)	(.099)	(.100)
Communication	.040	.040	.131	.126	.100*	.097*	-.129	-.160
	(.049)	(.049)	(.167)	(.168)	(.041)	(.041)	(.139)	(.140)
Air conditioner	.223*	.221*	.071	.075	.023	.021	.107	.110
	(.090)	(.090)	(.281)	(.284)	(.084)	(.084)	(.288)	(.289)
Motorized vehicle	-.014	-.021	.151	.120	.068	.063	.245	.222
	(.057)	(.057)	(.181)	(.184)	(.050)	(.050)	(.156)	(.158)
COVARIATES								
Age	.371**	.370**	1.258**	1.253**	.246*	.244*	.232	.262
	(.123)	(.123)	(.411)	(.412)	(.098)	(.098)	(.330)	(.336)
Age^2	-.003***	-.003***	-.004**	-.003**	-.001**	-.001**	-.002	-.002
	(.000)	(.000)	(.001)	(.001)	(.000)	(.000)	(.001)	(.001)
Married	-.084	-.085	.044	.068	.169	.163	-.247	-.279
	(.100)	(.100)	(.370)	(.374)	(.116)	(.116)	(.411)	(.411)
Smoke	-.344***	-.343***	-.322	-.321	-.188	-.186	-1.024	-1.084
	(.067)	(.067)	(.222)	(.224)	(.189)	(.189)	(.676)	(.682)
Education (No education)								
Primary	.058	.059	.279	.306	.095	.093	.018	.024
	(.149)	(.149)	(.596)	(.607)	(.092)	(.092)	(.281)	(.285)
Secondary	.159	.157	.187	.240	.044	.051	.222	.222
	(.192)	(.192)	(.685)	(.698)	(.151)	(.151)	(.451)	(.453)
College and above	.072	.076	.018	.092	-.293	-.286	.438	.431
	(.243)	(.243)	(.896)	(.912)	(.220)	(.220)	(.786)	(.786)
Log household income	.043†	.042†	.077	.084	.006	.007	-.085	-.088
	(.023)	(.023)	(.064)	(.065)	(.021)	(.021)	(.075)	(.075)
MEDIATE VARIABLES								
Dietary intake (per 1,000 kcal)		-.006		-.034		-.002		-.001
		(.021)		(.097)		(.027)		(.093)
Light occupational activity		-.118		-.215		-.186**		-.376†
		(.071)		(.221)		(.062)		(.210)
Exercise (per 100 metabolic equivalents, METs)		-.007		-.317		-.210		-.045
		(.129)		(.422)		(.183)		(.759)
Home activity (per 100 METs)		.046		.363		.168**		.281
		(.126)		(.451)		(.056)		(.186)
Bicycle/walk (per 100 METs)		-.794		2.025		.729		.795
		(.894)		(2.347)		(.672)		(1.851)
Constant	16.851***	16.967***			18.112***	18.191***		
Observations	9,104	9,104	1,238	1,238	10,307	10,307	1,469	1,469
Number of id	5,140	5,140	442	442	5,365	5,365	484	484

Standard errors in parentheses*** p<.001, ** p<.01, * p<.05, † p<.10
All models were adjusted for survey year.