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**Original Article**

# Are Entrepreneurs More Likely to Be Obese?

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**Abstract**

**Background:** Entrepreneurs not only promote a nation's economic growth but also increase employment. The risk of obesity among entrepreneurs may bring heavy economic burdens not only to the entrepreneurs but also to the national health care system. We aimed to examine the association between entrepreneurship and the risk of obesity.

**Methods:** We utilized data from the 2015 Harmonized China Health and Retirement Longitudinal Survey, including 2,802 individuals aged between 45 and 65 with complete data. This study used BMI (Body Mass Index) ($kg/m^2$) as an indicator of obesity risk. Entrepreneurs were defined as those respondents who run their own businesses as main jobs. We used multivariate OLS regression models and Bayesian Markov Chain Monte Carlo (MCMC) method to examine the link of entrepreneurship and obesity risk.

**Results:** The multivariate OLS regression results showed that entrepreneurship was positively associated with BMI ($P<0.01$). The Bayesian MCMC results indicated that the posterior mean was (0.597, 90% HPD CI: 0.319, 0.897), demonstrating that entrepreneurship was indeed significantly positively associated with the risk of obesity.

**Conclusion:** Being an entrepreneur is positively associated with the risk of obesity. As obesity can cause diseases such as hypertension, diabetes, coronary heart disease and stroke, the health departments should take necessary health interventions to prevent entrepreneurs from being obese in order to increase their entrepreneurial success.

**Keywords:** Entrepreneurs; Obesity; Body mass index; Bayesian; China

## Introduction

Entrepreneurs not only promote a nation's economic growth but also increase employment. However, starting a new business is a highly challenging job, it often requires entrepreneurs to pay more than ordinary efforts to cope with various crises as usually there are only limited resources available to entrepreneurs. Challenges will undoubtedly bring entrepreneurs various pressures, which may result in various health risks, one of which is obesity risk.

Currently there is no international consistent conclusion about the impact of entrepreneurship on health. Some scholars believe that because entrepreneurs face much higher work pressure than employees, they are more prone to various health risks. In the U.S. (1) and Sweden (2), entrepreneurship had a significant negative impact on mental health. A study in France (3) showed that the prevalence of diseases such as heart disease among entrepreneurs was significantly higher than that of non-entrepreneurs. But some other scholars believe that entrepreneurship can reduce stress and improve health. Studies in the U.S. (4) and Australia (5) found that entrepreneurs significantly reduced work stress because of the higher autonomy of entrepreneurs at work. In Sweden (6), the prevalence of diseases such as heart disease among entrepreneurs was significantly lower than that of non-entrepreneurs.

Obesity was closely associated with various health risks such as hypertension, diabetes, coronary heart disease and stroke (7). In China, the total medical expenses of hypertension, diabetes, coronary heart disease and stroke attributable to overweight and obesity totaled $2.74 billion, accounting for 25.5% of the total direct medical expenses of the four diseases, and 3.7% of the total national medical expenditure in 2003 (8). In China, direct health expenditures for overweight and obese people over the age of 45 were significantly higher than those for normal weight (9). Compared with normal-weight individuals, overweight and obese people were 15.0% and 35.9% more likely to be ill. The average health expenditure of an obese individual was on average 14.2% higher than that of a non-obese one.

Given this reality, if the risk of obesity among entrepreneurs is neglected and unchecked, it may bring heavy economic burdens not only to the entrepreneurs but also to the national health care system. We thereby raise a simple question: are entrepreneurs more likely to be obese? In order to answer this question, this study aimed to examine the association between entrepreneurship and BMI by establishing a rigorous mathematical model and using the Bayesian Markov Chain Monte Carlo (MCMC) method, using data from China Health and Retirement Longitudinal Study (CHARLS). Such a research would provide valuable and essential information for future health interventions that aim to prevent the obesity risk among entrepreneurs.

## Materials and Methods

### *Data*

The China Health and Retirement Longitudinal Study (CHARLS) is a project operated by Peking University, and it is a longitudinal study of individuals over age 45 in China. The data used in this study was 2015 Harmonized CHARLS data, which was a user friendly version of 2015 CHARLS data created by the University of Southern California. In 2015, the sample of CHARLS covered 150 counties and 450 communities (villages) in 28 provinces (municipalities, autonomous regions), and 23,000 respondents out of a total of 12,400 households.

The data includes information such as the health status, work status, gender, education level, marriage, and family income of the respondent. Data was available at http://charls.pku.edu.cn/zh-CN/page/data/harmonized_charls.

For the purposes, this study limited the sample to respondents who were working and aged less than or equal to 65 years, and complete data were available for them. Our final sample included 2,802 participants (1,765 men and 1,040 women), of whom 2,044 were rural residents and 761 were urban residents.

### *Variables*

The outcome variable in this study was the Body Mass Index (BMI), which was one of the most widely used indicators of overweight and obesity. BMI ($kg/m^2$) was calculated as the weight (in kg) divided by the height (in m) squared. The height and weight consisting of BMI were measured by the trained interviewer of CHARLS following strict procedures. For the measurement of height, the respondent was asked to stand erect on the floor board of the stadiometer with his back to the vertical backboard of the stadiometer, evenly distribute weight on both feet, place the heels of the feet together with both heels touching the base of the vertical board, place the feet pointing slightly outward at a 60°, maintain head in the Frankfort Horizontal Plane position. For the measurement of weight, the respondent was asked to stand on the weight scale with shoes off. The work-related explanatory variables include entrepreneur, work income, and working hours. Entrepreneur was the core variable of this study. The Harmonized CHARLS has a variable (r4slfemp) that specifically identifies whether the respondent was running his or her own business as a main job in 2015. We define those whose main jobs were doing their own business as entrepreneurs and those not as non-entrepreneurs. Working time refers to the total number of working hours per week of the respondent, and it can indicate the work pressure of the respondent. Work income refers to the personal income (after tax) from the respondent's work.

Socioeconomic status was closely related to obesity (10-12). Therefore, this study uses a number of control variables that reflect socioeconomic status: gender, age, hukou types, education, marital status, and whether or not children living together with the respondent. Hukou is a special legal registration document in China that can be grouped into two types (1=agricultural, 0=non-agricultural), the holders of the former ones usually live in the rural areas. In Harmonized CHARLS the educational level was categorized into 10 categories (1=illiterate, 2= incomplete primary school, 3=private home school, 4=elementary school, 5=middle school, 6=high school, 7=vocational school, 8=college, 9=university, 10=post-graduate, including master's and doctoral degrees). Marital status was dichotomized as married or non-married, with non-married including those partnered, divorced, widowed, never married or separated.

Lifestyle habits such as smoking and drinking were associated with obesity (13-15). The health and lifestyle control variables related to obesity were self-evaluated health (SEH), number of illnesses, smoking and drinking frequency. In CHALRS each respondent was asked about his or her self-evaluated health status. The SEH in this study was classified into five categories (1=not good, 2=normal, 3=good, 4=very good, 5=excellent). This study defines the number of visits to the hospital in the previous month of the interview as the number of illnesses. Alcohol intake was determined by frequencies of drinking (non-drinkers or never drinking during last year were treated as zero). Smoking status was indicated by the number of cigarettes smoked per day (nonsmoking is treated as zero).

### *The Analytical Model and Strategy*

First, we reported all explanatory and control variables as mean and SD (standard deviation). Then, we conducted traditional multivariate regression analysis to examine the effects of being an entrepreneur on BMI, adjusting for all or some of the cofounding variables. Finally, we conducted the Markov Chain Monte Carlo analysis to reexamine and verify the association between entrepreneurship and BMI. All analyses were performed using Statistical/Data Analysis software package STATA/MP 15.0.

In this study, the dependent variable BMI is a continuous variable. Traditionally, we use the following OLS model for analysis:

$$\boldsymbol{y}|\boldsymbol{\beta},\sigma^2,\boldsymbol{X}\sim N(\boldsymbol{X\beta},\sigma^2\boldsymbol{I}) \quad [1]$$

In equation [1], $N$ represents a Gaussian normal distribution, $\boldsymbol{y}$ and $\boldsymbol{X}$ are dependent variables and independent variables, respectively, beta is the parameter to be estimated in the model, $\boldsymbol{I}$ is the identity matrix, and $\sigma^2$ is the variance of the random terms in the model. The conditional likelihood function of the model is:

$$L(\boldsymbol{\beta},\sigma^2|\boldsymbol{y},\boldsymbol{X}) = (2\pi\sigma^2)^{-n/2}exp\left[-\frac{1}{2\sigma^2}(\boldsymbol{y}-\boldsymbol{X\beta})^T(\boldsymbol{y}-\boldsymbol{X\beta})\right] \quad [2]$$

The maximum likelihood estimate of the parameter beta can be obtained using equation [2]. However, compared with the Bayesian estimation method, the maximum likelihood method is not the most effective estimation method. Since the Bayesian estimation method can incorporate prior information into existing sample information, a more efficient parameter estimation can be acquired. Specifically, if the prior distribution of the parameter beta is known as $\pi(\beta,\sigma^2|X)$, then the posterior distribution of the parameter beta is:

$$\pi(\boldsymbol{\beta},\sigma^2|\boldsymbol{y},\boldsymbol{X}) \propto f(\boldsymbol{y}|\boldsymbol{\beta},\sigma^2,\boldsymbol{X})\pi(\boldsymbol{\beta},\sigma^2|\boldsymbol{X})$$
[3]

The use of the MCMC (Markov Chain Monte Carlo) method is one of the effective methods for obtaining posterior samples. For the parameter beta to be evaluated, we can think of it as a discrete Markov chain. If the transition probability matrix of the Markov chain is assumed to be A, the MCMC method can be used to obtain the Markov chain sample. If the Markov chain converges to the steady state $\pi(\boldsymbol{\beta}|\boldsymbol{y},\boldsymbol{X})$, then the Markov chain can be treated as a sample of the posterior distribution of the parameter beta in equation [3]. One of the sampling algorithms is the Gibbs algorithm firstly proposed by Geman (16). The Gibbs sampling algorithm allows sampling from the conditional distribution of each parameter under certain conditions when the model is a multivariate one; therefore, it is one of most widely used sampling algorithms (17).

## Results

The average BMI index of respondents in 2015 was 24.309, therefore, most of the respondents were at the brink of being overweight according to the World Health Organization (WHO) criteria (18) (Table 1). Only nearly 20% of the respondents were entrepreneurs. Males accounted for the majority in the sample.

**Table 1:** Descriptive Characteristics of Participants, mean (Standard Deviation)

| *Variable* | *All* | *Entrepreneurs* | *Non-entrepreneurs* | *t-test* |
|---|---|---|---|---|
| BMI | 24.309(3.668) | 24.786(3.461) | 24.200(3.706) | -3.285*** |
| Entrepreneur | 0.185(0.388) | - | - | |
| Work Income (ln) | 9.553(1.225) | 9.554(1.520) | 9.552(1.148) | -0.034 |
| Work hours (ln) | 3.765(0.611) | 3.802(0.658) | 3.757(0.600) | -1.51 |
| Gender | 0.629(0.483) | 0.643(0.480) | 0.626(0.484) | -0.713 |
| Age | 52.448(6.343) | 51.788(6.084) | 52.598(6.392) | 2.628*** |
| Hukou | 0.728(0.445) | 0.703(0.458) | 0.734(0.442) | 1.457 |
| Education | 4.219(1.677) | 4.106(1.479) | 4.244(1.717) | 1.694* |
| Marital Status | 0.955(0.207) | 0.954(0.210) | 0.955(0.207) | 0.166 |
| Children Living Together | 0.636(0.481) | 0.649(0.478) | 0.633(0.482) | -0.664 |
| SEH | 2.488(0.956) | 2.479(0.989) | 2.490(0.949) | 0.240 |
| Number of illness | 0.319(1.104) | 0.249(0.773) | 0.335(1.165) | 1.592 |
| Drinking | 1.712(2.457) | 1.757(2.491) | 1.701(2.450) | -0.463 |
| Smoking | 6.808(11.265) | 7.023(12.061) | 6.759(11.079) | -0.481 |
| N | 2802 | 518 | 2284 | |

Notes: Standard deviation in parentheses. *$P$<0.10; **$P$< 0.05; ***$P$<0.01

The average education level of the respondents was lower than the middle school level, signaling a general low education level of the respondents. Most of the respondents were married and more than half of the respondents had children living with them. The average respondent's working time was about 50 h per week, indicating overtime work was common in China. The average self-reported health of the respondents was 2.488, indicating that most of the respondents thought their health was between normal and good. The average number of visits to doctors by respondents in the previous month was less than one. Respondents on average smoked nearly seven cigarettes a day, and drank at least once but no more than 3 times a month. The health status and health habits of most of the respondents were not optimistic.

Table 1 also gives a descriptive statistical analysis of the difference between entrepreneurs and non-entrepreneurs, where the t-test is a test for whether there is a significant difference in the mean of the variables in the two groups. We can observe that the average BMI of the entrepreneurs is higher than the corresponding value of the non-entrepreneurs, and the difference in the mean value of the BMI is significant ($P$<0.01). There was no significant difference in work income and working hours between the two groups. The average age of entrepreneurs is lower than the average age of the employees, and this age difference is also significant ($P$<0.01). In addition, the average education level of both groups are below junior high school level, but entrepreneurs' education levels are even lower than those of non-entrepreneurs, and the difference in education level is weakly significant ($P$<0.10). There is no significant difference in the mean of the remaining variables.

Table 2 shows the OLS multivariate regression results of four models. In Model 1, the coefficient of entrepreneur is 0.5862 and significant ($P$<0.01), which indicates that being an entrepreneur will significantly increase one's BMI.

**Table 2:** Multivariate OLS Regression Results

| *Variables* | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|
| Entrepreneur | 0.5862*** | 0.5878*** | 0.5928*** | 0.5954*** |
| Work Income | - | 0.0382 | - | 0.0540 |
| Work Hours | - | - | -0.2044* | -0.2175* |
| Gender | 0.1750 | 0.1543 | 0.1764 | 0.1472 |
| Age | -0.0148 | -0.0130 | -0.0171 | -0.0148 |
| Education | 0.0876* | 0.0833* | 0.0837* | 0.0773* |
| Marital Status | 0.2932 | 0.2885 | 0.2813 | 0.2738 |
| Children Living Together | -0.1111 | -0.1093 | -0.1240 | -0.1223 |
| Hukou | -0.6294*** | -0.6142*** | -0.6247*** | -0.6030*** |
| SEH | 0.0839 | 0.0793 | 0.0856 | 0.0792 |
| Number of illness | 0.1384** | 0.1391** | 0.1336** | 0.1343** |
| Smoking | -0.0281*** | -0.0281*** | -0.0280*** | -0.0280*** |
| Drinking | -0.0193 | -0.0191 | -0.2044 | -0.0181 |
| Constant | 24.7160*** | 24.2948*** | 25.6321*** | 25.0943*** |
| Adjusted $R^2$ | 0.0207 | 0.0205 | 0.0215 | 0.0214 |
| $P$-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Notes：*$P$<0.10; ** $P$<0.05; ***$P$<0.01

In other words, entrepreneurs are more likely to be overweight or obese than non-entrepreneurs. The coefficient of the education is only weakly significant ($P$<0.10), and the absolute value of the coefficient is small too, so its impact on the BMI index is rather limited. The coefficient of Hukou is -0.6294 and significant ($P$<0.01), indicating that having an agricultural Hukou will significantly reduce a person's risk of obesity. In China most people who have agricultural Hukou live in rural areas and often participate in some physical farming activities, which will have a positive impact on reducing the risk of obesity. The coefficient of the number of illnesses is positive and significant ($P$<0.05), meaning that the more times a person is ill, the more likely it is to be an obese person. Slightly surprised, the smoking coefficient is negative and significant ($P$<0.01), which means that smoking may have a weight loss effect, but because the absolute value of the smoking coefficient is small, the weight loss effect of smoking is extremely weak. The coefficients of the remaining variables are not significant. The work income variable was added to Model 2, but the coefficient of it was not significant, indicating that work income had no significant effect on obesity. Model 3 includes working hours, which has a coefficient of -0.2044 and is only weakly significant (*P*<0.10). When both work income and work hours are added into model 4, we find that the coefficient estimate and significance of the working hours in Model 4 remain unchanged compared with Model 3. Compared with Model 2, the coefficient estimate and significance of the work income variable in Model 4 remain unchanged. Finally, in the four models, the size and significance of the entrepreneur coefficients remain essentially unchanged.

We then use Stata15 software to simulate and estimate the parameters using MCMC's Gibbs sampling method. The prior distribution uses the information-free prior distribution. The number of iterations is set to 12,500 times and the burn-in is 2,500. A sample of 10,000 iterations is used to estimate the value of the model parameters.

Table 3 gives the estimated results of the parameters obtained using the Gibbs sampling algorithm of MCMC.

**Table 3:** MCMC Model Gibbs Sampling Estimates

| *Variable* | *Posterior Mean* | *MC Error* | *Median* | *HPD CI (90%)* |
|---|---|---|---|---|
| Entrepreneur | 0.5972* | 0.0017 | 0.5980 | [0.3186,0.8965] |
| Work Income | 0.0548 | 0.0006 | 0.0551 | [-0.0490,0.1554] |
| Work Hours | -0.2156* | 0.0011 | -0.2161 | [-0.3959,-0.0260] |
| Gender | 0.1490 | 0.0018 | 0.1478 | [-0.1684,0.4425] |
| Age | -0.0149 | 0.0001 | -0.0149 | [-0.0348,0.0043] |
| Education | 0.0762 | 0.0005 | 0.0756 | [-0.0011,0.1509] |
| Marital Status | 0.2740 | 0.0033 | 0.2727 | [-0.2754,0.8217] |
| Children Living Together | -0.1242 | 0.0015 | -0.1242 | [-0.3577,0.1283] |
| Hukou | -0.6034* | 0.0017 | -0.6023 | [-0.8962,-0.3486] |
| SEH | 0.0789 | 0.0007 | 0.0786 | [-0.0481,0.1945] |
| Number of illness | 0.1353* | 0.0006 | 0.1340 | [0.0299,0.2356] |
| Smoking | -0.0280* | 0.0001 | -0.0280 | [-0.0391,-0.0166] |
| Drinking | -0.0181 | 0.0003 | -0.0182 | [-0.0712,0.0326] |
| Constant | 25.0907* | 0.0118 | 25.0898 | [23.1560,26.9403] |
| DIC | 15190.32 | | | |

Note*: P**<0.10

The second column gives the expected value of the marginal posterior distribution of the relevant parameters in the MCMC model, i.e. the posterior mean. The third and fourth columns give the MC error and the median, respectively. The fifth column gives the 90% maximum posterior density confidence interval (HPD CI), which is different from the confidence interval in the OLS regression. The HPD CI directly indicates that the probability that the parameter estimate falls within the interval is 90%. In addition, Table 3 also gives the DIC (Deviance Information Criteria) value of MCMC. We can see that compared with the OLS estimation method, the posterior mean of the entrepreneur parameter obtained by the MCMC method remain basically unchanged. Moreover, the MC error of the entrepreneur parameter is small, the median is very close to the posterior mean, and the posterior mean is significant (0.597, 90% HPD CI:0.319,0.897), indicating that entrepreneurship indeed significantly increases the risk of obesity. In addition, the posterior mean values of working hours (-0.2156, 90% HPD CI: -0.396, -0.026), Hukou (-0.603, 90% HPD CI: -0.896, -0.349), number of illness (0.135, 90% HPD CI: 0.0299, 0.2356), and smoking (-0.028, 90% HPD CI: -0.039,-0.017) are also significant, and the size and symbol are basically consistent with the OLS estimates. The only exception is the education variable. Although the posterior mean of education obtained by the MCMC method is basically the same as the OLS estimate, the posterior mean of education is not significant. This signals that the significance test results of education produced by OLS in Table 2 may be incorrect. In general, the Bayesian MCMC estimation method is more accurate than the results obtained by the ordinary OLS estimation method, and the MCMC estimation result can verify the validity of the OLS estimation results.

Figure 1 shows the diagnostic map of the entrepreneur parameter Markov chain obtained after 10,000 iterations using the Gibbs sampling algorithm of MCMC. The first to fourth quadrants given are histograms, trajectories, autocorrelation plots, and kernel density function graphs, respectively. The histogram shows that the marginal posterior distribution of the parameters of entrepreneur exhibits a normal distribution. The trajectory map is stable and shows that the Markov chain has a good mixture. The autocorrelation graph shows that there is basically no autocorrelation problem in the parameters of entrepreneur. Finally, the density of the MCMC full sample, the first 50% sample and the last 50% sample basically overlap, indicating that the Markov chain mixing and convergence are good. In sum, the diagnosis of Figure 1 verifies that the Gibbs sampling algorithm employed herein is effective.

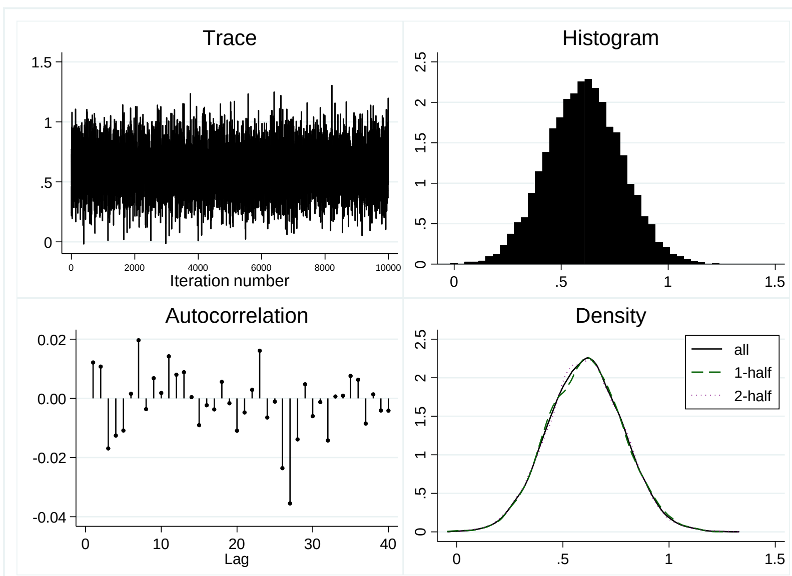


**Fig. 1:** Diagnostic map of the entrepreneur parameter Markov chain

In addition, we tested the robustness of our results. Firstly, we used the 2013 Harmonized CHARLS data to perform the same regression analysis as in Table 3 and found that the conclusion that entrepreneurship significantly increased the risk of obesity remained unchanged. Secondly, we used the alternative M-H sampling method to estimate the MCMC model in Table 3 and found that the Markov chain of the entrepreneur parameter still had good mixing and convergence, which was consistent with the estimation result of the Gibbs sampling method.

## Discussion

Based on Harmonized CHARLS data, the effects of entrepreneurship on obesity were empirically analyzed using multivariate OLS linear regressions and Bayesian MCMC. Entrepreneurs are more likely to be obese than non-entrepreneurs.

This finding is consistent with the claims that entrepreneurs are more prone to various health risks as many studies provided evidence that work stress was closely related to the risk of obesity. In the U.K. (19), work stress reduced the weight of men with low BMI and increased the weight of men with high BMI, but had no significant effect on weight of women. In U.K. (20) long-term work stress significantly increased the risk of obesity and central obesity. In the United States, the mental stress generated at work significantly increased the weight of men and women with high BMI index (21). One study (22) in 13 European countries found that work stress was significantly associated with BMI, and higher work stress was associated with higher risk of obesity.

In the case of work hours, the results of our study indicated that the increase in working hours was negatively associated with the risk of obesity. The result is a little surprising because usually, the longer a person works, and the greater is the stress. The higher is the stress, the more likely it is to have poor health. However, in U.K. (23), long working hours could be negatively associated with health risks for those workers who had high social support. In our case, we think the negative association could be explained by the average low education level of the respondents in this study. People with low education level are more likely to be engaged in work that requires a large or certain amount of physical activity. The appropriate increase in physical activity helps to reduce stress, so the increase in working hours may actually reduce a person's obesity in our study.

This study also found that work income was not significantly related to risk of obesity. This finding was in compliance with previous research (24), in which, the relationship between work income and stress was uncertain: on the one hand, higher work income allowed respondents not to have to worry about their clothes, food, housing, travel, etc., which would reduce the pressure on respondents; but on the other hand, higher work income also meant more work responsibilities, which would increase the respondents' pressure.

## Conclusion

Being an entrepreneur will significantly increase the risk of obesity. The Bayesian MCMC is a more effective estimation method than the ordinary multivariate OLS estimation method. Obesity can lead entrepreneurs into a vicious cycle of health, because obesity can cause commonly high-disability and high-mortality diseases such as hypertension, diabetes, coronary heart disease and stroke, which not only directly impair the health of entrepreneurs, make the entrepreneurs partially or completely lose their ability to work, bring heavy medical burdens to the entrepreneur and the whole health care system, but also indirectly reduce the quality of human capital in the whole society, and ultimately lead to a decline in economic growth. Therefore, the health departments should take necessary health interventions to prevent entrepreneurs from being obese, which will not only enable entrepreneurs to have better health, but also enable entrepreneurs to run their businesses with higher efficiency, thereby increasing the possibility of entrepreneurial success and producing a positive impact on national economic growth.

## Ethical Considerations

This analysis uses data from the Harmonized CHARLS (China Health and Retirement Longitudinal Survey) dataset. All participants in CHARLS signed written informed consent.

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## Conflicts of interest

The authors declare no conflict of interest.

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