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RESEARCH ARTICLE

Who is chronically obese in Indonesia? The role of individual preferences

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Abstract

Numerous studies have confirmed the relationship between individual risk and time preference and obesity. Nevertheless, none has studied the effect of these attitudes on chronic (long-term) obesity. This study used Indonesia Family Life Survey (IFLS) data from 16,366 individuals. It tracked their obesity status in 2007 and 2014 by calculating body mass index, the ratio between body weight and square of height. Besides the conventional risk-averse and risk-tolerant behaviour, the IFLS sample includes people who fear uncertainty related to the status quo bias. The ordered logit regression results show that past impatience, risk tolerance, and status quo bias behaviour (in 2007) are associated with transient or chronic obesity, while only current behaviour of status quo bias (in 2014) is associated with obesity. Furthermore, our study confirms that chronic obesity in Indonesia is prevalent among highly educated, high-income, and urban-centric individuals, exacerbated by impatience, risk tolerance, and uncertainty aversion. Thus, providing information on the risk of obesity and food calories, giving the incentive to avoid obesity, and improving the quality of built environments such as public parks, public transportation, and footpath could help prevent the rising obesity prevalence.

Keywords: chronic obesity; risk preference; time preference; status quo bias

JEL Classification: I12; I15; D9

Introduction

The prevalence of obesity and overweight is increasing worldwide; this is happening in both developed and developing countries. World Health Organization (WHO) estimated that obesity has nearly tripled since 1975. Obesity is a major risk factor for various diseases such as heart disease and stroke, diabetes, musculoskeletal diseases, especially osteoarthritis, and various cancers (World Health Organization, 2018). WHO considers a body mass index (BMI) of over 30 as obesity. However, in Asia-Pacific countries, there is usually a cut-off point that differs from the WHO's definition. The Indonesian Ministry of Health defines obesity as a BMI over 27, and this study follows that specific cut-off instead of the WHO's definition. From 2007 to 2018, the prevalence of overweight ($25 \leq BMI < 27$) in Indonesia increased from 8.6% to 13.6%, while obesity prevalence ($BMI \geq 27$) increased from 10.5% to 21.8% (Kementerian Kesehatan, 2018). These facts indicate that obesity has become a global public health problem with an increasing trend.

As in developed countries, developing countries have shifted to food with more fat, meat, added sugars, and bigger portion sizes. It has been happening in higher and lower socioeconomic strata in recent years. Besides the change in diets, reduction in physical activity is linked to several factors: more sedentary activity in farming and forestry, a rise in jobs that are largely done by sitting in front of a computer, and patterns of leisure activities that do not require high physical activity (Bhurosy and Jeewon, 2014). Evidence from African regions showed that the decreasing trend of physical activity could partly explain the prevalence of obesity since the late 1980s (Samuel and Atinmo, 2008). Low physical activity is also driven by inadequate facilities, such as a lack of safe pathways, bicycle paths, and playgrounds (Turconi *et al.*, 2008). Papas *et al.* (2007) noted that many studies found that the lack of access to a well-built environment that encourages people to do more physical activities, such as sidewalks, parks, recreational facilities, and public transportation, strongly correlates with overweight/obesity. Looking at evidence from Indonesia, increasing access to the nearest bus stop from residency could reduce gasoline consumption (Abe and Kato, 2014), which could subsequently be associated with reduced obesity prevalence (Frank *et al.*, 2004). High-density and diverse land-use urban settings adversely affect physical activity engagement in Indonesia, reflecting the common issue in developing countries caused by inadequate urban planning (Muzayanah *et al.*, 2022).

There is a strong association between obesity and socioeconomic conditions in developing and developed countries. In developed countries, obesity is more prevalent among people of lower socioeconomic status, while in developing countries, obesity rises with economic development (Dinsa *et al.*, 2012; Pampel, 2012; Wang and Beydoun, 2007). In developing countries, poverty and manual labour reduce food intake and increase energy expenditure, making the poor less likely to be obese. The rich in developing countries face increased risk due to surplus food and reduced physical activity. In developed countries, the poor consume energy-dense diets due to limited access to low-calorie options and a more sedentary lifestyle due to urbanisation and technology. The wealthy, who are more health-conscious, can better prevent obesity through a healthy diet and exercise. The relationship between obesity and socioeconomic status in Indonesia seems to follow the pattern in developing countries. Despite the prevalence of food scarcity in some regions, urbanisation and an increase in sedentary lifestyles have increased obesity rates, particularly among the more affluent population.

Pengpid and Peltzer (2017) detected several characteristics positively associated with obesity in Indonesia, such as being female, aged 30–59 years, having high education, having high socioeconomic status, and living in urban residences. From a behavioural perspective, it is certainly interesting to know how one's preferences play a role in becoming obese. The fundamental question of obesity is: why would individuals decide, or happen, to be fat? (Mann, 2008). Risk and time preference are two types of economic preferences that are often used to explain how decisions are made. Examining people's evaluation of risk and inter-temporal trade-offs that could influence health decisions is essential to better understanding individuals' health decision-making mechanisms.

Risk preference refers to the degree of an individual's tolerance to risk/uncertainty (e.g., would you take option A: \$50 for sure, or would you take option B: a 50:50 chance of receiving \$25 or \$75?). The conventional classification of risk preference is risk-averse, risk-neutral, and risk-loving. A person with a higher risk tolerance will be more likely to take the bet than a risk-averse person. In contrast, a risk-neutral person will decide based on the expected value of each option (in this case, a risk-neutral person will be indifferent between options A and B). Meanwhile, time preference refers to the extent to which higher rewards received later are preferred over immediate and smaller rewards (e.g., would you take \$50 now or \$100 1 year later?). The degree of an individual's patience/impatience is called the discount rate; a person with a 50% yearly discount rate will be indifferent between \$50 now and \$100 1 year later (i.e., money received 1 year later is worth half compared to today's money). Therefore, a higher discount rate translates into a higher degree of impatience.

When consuming excessive calories, a person risks contracting obesity-related diseases and considers the trade-off between the immediate pleasure of calorie consumption in the present and better health conditions in the future. Excessive calorie consumption might negatively impact

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individuals and society. Individuals will make suboptimal decisions if they decide on their calorie consumption under imperfect rationality. For example, time-inconsistent preference is when a person keeps delaying doing something beneficial in the future because when they make a decision, an action that gives instant benefit always seems preferable. Even when excessive calorie consumption is made rationally, market failures might occur due to negative externalities in the form of costs borne by the public, such as the additional health insurance costs to cover obesity-related illnesses. Therefore, the role of individual preference in influencing the prevalence of obesity should be of great interest in public health.

Several studies have used risk and time preference variables that affect addictive or unhealthy behaviours. Ida and Goto (2009) simultaneously measured risk and time preferences to analyse their relationship with the smoking pattern. Studies showed that risk and time preference explain some variance of addictive and unhealthy behaviour, such as dissaving, smoking, alcohol consumption, conduct at school, and obesity (Chabris *et al.*, 2008; Sutter *et al.*, 2013). Studies using risk and time preference in Indonesia are still quite limited. Using Indonesia Family Life Survey (IFLS) data, several studies used an Indonesian sample to look at the effect of risk and time preference on the choice between public and private sector employment, smoking habits, child vaccination, asymptomatic diseases, and entrepreneurship (Anandari and Nuryakin, 2019; Chowdhury, 2016; Diza *et al.*, 2022; Kim and Radoias, 2016; Sohn, 2017). To the best of the authors' knowledge, no study has directly linked risk and time preference to obesity using a representative sample from Indonesia's population.

There is growing literature about the relationship between obesity and risk and time preference. Brown and Biosca (2016) and Komlos *et al.* (2004) used data representing national populations, measuring time preference using saving patterns as their proxy. Both studies found that impatience had a positive association with BMI. De Oliveira *et al.* (2016), Dogbe and Gil (2019), and Sutter *et al.* (2013) used an experimental method to elicit risk and time preference. De Oliveira *et al.* (2016) found that more risk-tolerant individuals have higher BMI than risk-averse individuals. Dogbe and Gil (2019) and Sutter *et al.* (2013) found that impatience is positively associated with BMI.

This research was conducted using IFLS data. In IFLS, risk and time preference are obtained directly by eliciting the two preferences. In previous studies of obesity that used nationally representative data, proxies were used to measure these preferences. Therefore, this study contributes to the obesity and risk and time preference literature by examining the relationship between risk and time preference obtained directly from elicitation (not using proxy measures) and obesity using nationally representative samples (not small-scale experiments). By using longitudinal data, this study could be distinguished from previous research by the construction of chronic obesity, defined as being obese in both survey years in 2007 and 2014, and transient obesity, defined as being obese in one of the survey years. These definitions follow Mustillo *et al.* (2003) who studied chronic obesity among children in the USA.

Utilising the unique nature of the risk preference questionnaire in the IFLS, we identify individuals who do not follow the standard expected utility theory (risk-averse, risk-neutral, and risk-loving classification), especially individuals who choose a weakly dominated option. In this case, when given two options for receiving money, the respondent prefers the option with a certain amount of money to an option with a probability of getting a higher or lower amount. However, the latter option's lower amount is worth the same as the certain option's (e.g., option A is $50 for sure, while option B is a 50:50 chance of receiving either $50 or $100, and the respondent chooses option A). Those individuals are labelled as 'uncertainty averse' as an alternative classification of risk preference in addition to the conventional risk-averse and risk-tolerant individuals. Differing from risk-averse individuals, uncertainty-averse individuals might perceive having to deal with probability as something costly.

To estimate the effect of individual risk and time preference on obesity, ordered logit regression is used given the ordinal nature of our obesity variable (chronically obese, transiently obese, and never obese). After controlling for some important covariates, such as demographic and lifestyle factors, it was found that both risk and time preference have a role in determining the probability of being chronically or transiently obese. Past impatience and risk tolerance behaviour is associated with obesity, but current behaviour is not associated. One of the novel findings from this study is that uncertainty aversion increases the probability of being transiently or chronically obese. The rationale of this finding is that individuals more reluctant to face uncertainty might also not want to change their status quo, which is having an unhealthy lifestyle. This behaviour leads them to maintain habits that increase the probability of being obese compared to individuals unwilling to face uncertainty. Some demographic and lifestyle factors also contribute to the higher probability of being obese such as being female, being married, having a university degree, higher spending allocation on fish and meat, and living in urban areas.

Literature review

Overweight and obesity are defined as excess body fat accumulation that can harm health. The fundamental cause of obesity is an energy imbalance between calories consumed and calories expended. Globally, there has been an increase in foods with high fat and a decrease in physical activity due to changes in lifestyle in modern times (World Health Organization, 2018). Philipson and Posner (1999) argued that technological change causes a decrease in the cost of consuming calories. Thus, the increase in body weight has been occurring because of increased calorie consumption caused by modernisation. However, Ritchie and Roser (2017) showed that global trends in the consumption of calories are heading towards convergence, which means that countries with high levels of calorie consumption are no longer increasing their consumption.

On the other hand, there is a change in the intensity of physical activity in daily work so that daily work no longer demands many calories, leading to increased demand for weight loss. Although the demand for weight loss has increased, the decrease in physical activity due to work patterns might still be more dominant. Komlos *et al.* (2004) argued that a complementary factor increases obesity: time preference. In addition to time preference, individual risk preferences have essential effects on consumption decisions (Dogbe and Gil, 2019). Therefore, this study will analyse the role of risk and time preference in the obesity phenomenon.

Uncertainty is usually inherent in decision-making, and a choice can have various consequences. Many actions can cause a person to become unhealthy, such as smoking, alcohol consumption, and excessive calorie consumption. In deciding to take an unhealthy behaviour, the individual considers his satisfaction in doing harmful activities and the subsequent possibility of becoming ill. In the context of overweight and obesity, a person decides their calorie intake by considering the satisfaction of consuming foods and the negative consequence of being overweight/obese, which is the possibility of getting an obesity-related illness. Regarding the relationship between time preference and obesity, one must give up current calorie consumption for future health to maintain weight. So, how much a person values the future will determine how much consumption they will be willing to give up. Offer (2001) said that for an increase in body weight, one needs to prefer immediate enjoyment of food consumption to normative appearance (ideal body weight) in the future.

Data and methods

This study used individual and household-level data from IFLS5 and IFLS4 conducted in 2014 and 2007. IFLS is an ongoing, multipurpose household longitudinal survey in Indonesia that represents 83% Indonesian population, including more than 30,000 respondents spread across 13 provinces in Indonesia. Starting in 1993, IFLS has been conducted five times. The latest wave, IFLS5, was conducted in 2014. The data used in this study are:

- Individual's height and weight to measure obesity as the dependent variable.
- Individual risk and time preferences as the main interest variables.
- Age, marital status, number of household members, gender, educational attainment, physical intensity of work, wealth, residence, access to drinking water and sanitation, smoking habits, physical activity, and food expenditure as confounding variables.

The dependent variable is the persistence of obesity in 2014 and 2007 (never obese, transiently obese, chronically obese). As the dependent variable is created using two surveys, we have the option of using independent variables from either 2014 or 2007. Using 2014 variables seems more logical as recent experiences are likely to be better predictors of current obesity status rather than examining associations with patterns of behaviour from 7 years ago. However, there is also a rationale for using the dependent variable from the previous survey: BMI is an outcome of individual habits accumulated over a period, and the proposition is that the outcome realised in the current year is an accumulation of daily activities influenced by characteristics of the past. Therefore, to complement both arguments, we regress the obesity status separately on both independent variables in 2014 and 2007 and analyse the differences.

The most standard measurement of obesity is BMI, the ratio between body weight in kilograms and square of height in metres (kg/m^2). BMI is the most popular parameter because of its ease of measurement. Although commonly used, BMI is considered to have the disadvantage of not distinguishing between non-fat and fat mass in the body. Burkhauser and Cawley (2008) used percent body fat and total body fat. Their study showed that BMI results in inaccurate obesity classification relative to percent body fat. They also found that total body fat positively correlates with unemployment, while BMI cannot explain the correlation. From the IFLS data, waist and hip circumference could be obtained to construct waist circumference and waist-hip ratio (WHR) as an alternative to BMI. However, the use of waist circumference and WHR, which are only recorded for respondents over the age of 40, may cause a sample selection problem and produce an inference that is not representative nationally. Therefore, although it is realised that BMI has weaknesses, this study still uses only BMI as the parameter of obesity.

WHO defines obesity as a BMI above 30, while the Indonesian Ministry of Health defines obesity as a BMI of more than 27. Using the Indonesian BMI cut-off, this study modelled obesity status into an ordinal variable valued 0 for respondents who were never obese, 1 for respondents who were obese in one of the survey years (transiently obese), and 2 for respondents who were obese in both of the survey years (chronically obese). This approach allowed the analysis of whether risk and time preferences affect the persistence of obesity in an individual.

Other covariates of obesity are needed as cofounding variables to fulfil the conditional independence assumption of the regression of risk and time preference on obesity. Using IFLS data, Pengpid and Peltzer (2017) found some characteristics positively associated with obesity, such as being female, aged 30–59 years, highly educated, having high socioeconomic status, and living in urban areas. Aizawa and Helble (2017) also used IFLS data to analyse socioeconomic inequality in excessive body weight by considering several covariates such as demographic characteristics (age, marital status, and the number of family members, education), wealth, access to sanitation, employment, and consumption of staple foods, meat and fish, soft drinks, oil, and food purchased outside the home. Therefore, this study used confounding variables based on demographic factors (age, marital status, number of household members, and gender) and lifestyle and environmental factors (physical intensity of work, physical activity, wealth, residence, access to drinking water, and sanitation, smoking habits, and percentage of food expenditure).

Elicitation of risk preference

Elicitation of risk preference was obtained from the Risk and Time Preference Section of book 3A of the IFLS module. In this section, there are two sets of questions in which the respondent is given

Table 1. Risk Preference Classification

Risk preference	Set 2 score			
Set 1 score	0	1	2	3
0	RA	RA	Inverted s utility	Inverted s utility
1	RA	RA	Inverted s utility	Inverted s utility
2	RT	RT	RT	RT
3	RT	RT	RT	RT

Note: RA = Risk-averse; RT = Risk-tolerant

two choices: definite choice and choice with probabilities. An example of these questions is as follows (from the first set):

> 'Suppose you are offered two ways to earn some money. With option one, you are guaranteed Rp.800 thousand per month. With option two, you have an equal chance of either the same income, Rp.800 thousand per month, or, if you are lucky, Rp.1.6 million per month, which is more. Which option will you choose? (1) Rp.800 thousand per month or (2) Rp.1.6 million or Rp.800 thousand per month'.

The first question in each set is used to determine whether the respondent 'understands' the question. Option (1) should be weakly dominated by option (2) based on the expected utility. If the respondent chooses option (1) in the question above, the interviewer will re-explain the question. If, after being re-explained, the respondent still chooses option (1), the respondent will proceed to the next set, and then the respondent will be classified as 'uncertainty averse'. Sohn (2016) labelled those respondents as 'risk incomprehensive', suggesting they do not understand the basic concept of risk.

It could be argued that it is pretty unlikely that every person who chooses option one fails to understand the basic concept of risk because more than half of the respondents who choose option one have at least completed senior high school. The term 'uncertainty effect', coined by Gneezy *et al.* (2006), which states that individuals could value a risky prospect less than its worst possible outcome, might also explain why some people choose option one on this question. Cao *et al.* (2011) label individuals who are more unwilling to take actions that impose risk than bear the risk of remaining passive as 'fear of the unknown/change'. Therefore, it is expected that 'uncertainty-averse' individuals are more likely to be obese. They are more reluctant to change their status quo, which is having an unhealthy lifestyle, even though changing to a healthier lifestyle might be less risky.

Respondents who choose option (2) will continue to question with higher risk. The second set has similar questions with higher risk compared to the first set. There are two alternative ways to calculate the amount of risk aversion from this set of questions. First, Sanjaya (2013) gave scores for each choice ranging from 0 to 2 for each set. The scores from both sets are added up so that the score is between 0 (most risk-averse) to 4 (most risk-tolerant). The second alternative to calculate risk aversion is to measure the Arrow–Pratt index of absolute risk aversion (ARA), as conducted by Sanjaya (2013) and Permani (2011). A higher ARA coefficient indicates a higher degree of risk aversion (see Permani (2011) for the detailed ARA calculation). This study follows Ng's (2013) scoring, which gave each set of scores ranging from 1 to 4 (adjusted to 0 to 3 in this study, see Ng (2013) for the detailed scoring for both risk and time preference).

A respondent has a 'consistent' ARA coefficient if she scores zero on set 2 and 0–3 on set 1 or scores three on set 1 and between 0 and 3 on set 2 (see Table 1). The respondent shows 'inconsistent' behaviour if he/she is risk-averse on set 1 but risk-tolerant on set 2 (e.g., ARA coefficient from set one is $0.125 \leq ARA \leq \infty$, but set 2 is $0.004 \leq ARA \leq 0.008$). This 'inconsistency' might be explained by the

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inverted s utility formulated by Friedman and Savage (1948), which demonstrates how individuals can be risk-averse at low income and risk-loving at high income. In other words, some people might be more willing to make a bet when they have a higher income than when they have a lower income (because the money involved in set 1 is substantially lower than in set 2).

Using ARA, this study categorised respondents into four groups: (1) those who have the inverted s utility, (2) risk-tolerant respondents who score more than or equal to two in one of the sets and choose 'consistent' choices, and (3) uncertainty-averse respondents, who choose the certain outcome in the first question while (4) the risk-averse respondents, who score less than to two in each set and choose 'consistent' choices, will be used as the reference group (see Table 1). Respondents with inverted s utility were dropped to simplify the risk preference classification because they only account for around 1% of the sample.

Elicitation of time preference

Similar to risk preference, time preference elicitation was obtained from book 3A. There are two sets of questions in which each respondent chooses between a hypothetical gift given today or in the next few years. An example of these questions is as follows:

> 'You have won a lottery and can choose between being paid: (1) Rp.1 million now, or (2) Rp.1 million in 1 year, Which do you choose?'.

As in the risk preference questions, the first question determines whether the respondent 'understands' the question. Respondents who choose option (2) thus prefer to delay receiving money, even without interest. If the respondent chooses option (2) in the question above, the interviewer will re-explain the question. If, after being re-explained, the respondent still chooses option (2), then the respondent will be classified as a 'negative time discounter', which means that the person prefers to receive the same amount of money later rather than now. Respondents who choose option (1) will continue to question with a higher amount for the delayed prize. The time preference questions are designed to capture a higher discount rate at each subsequent question so that respondents with a higher score are more impatient than respondents with a lower score. The second set has similar questions with a higher amount but a longer delay than the first set. This study refers to Ng (2013) to calculate the range of values of the annual discount rate of each question.

Like risk preference questions, a respondent only has a 'consistent' discount rate if she gets a zero score in set one and 0–3 in set two or gets a 3 in set two and a score between 0 and 3 in set one. Respondents who were impatient in set one but were patient in set two are categorised as 'naïve', behaving impatiently when the gift is delayed for a short time (1 year) but patiently when the gift is delayed for a long time (5 years).

The respondents are categorised into four groups: (1) naïve respondents, (2) impatient respondents, who score more than or equal to 2 in one of the sets and choose 'consistent' choices, and (3) negative time discounters, who choose to delay money without any interest rate in the first question of each set while (4) the patient respondents, who score less than to 2 in each set and choose 'consistent' choices, will be used as the reference group in the regressions (see Table 2). Respondents with naive and negative time discounter characteristics are dropped to simplify the time preference classification because they only account for around 1% and 2% of the sample.

Regression model

The ordered logit regression is as follows:

$$Y_i = \alpha_i + \beta_i RP_i + \gamma_i TP_i + \tau_i X_i + \varepsilon_i$$

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Table 2. Time Preference Classification

Time preference	Set 2 score			
Set 1 score	0	1	2	3
0	Patient	Patient	Impatient	Impatient
1	Patient	Patient	Impatient	Impatient
2	Naive	Naive	Impatient	Impatient
3	Naive	Naive	Impatient	Impatient

Y_i: obesity status; RP_i: risk preference dummies; TP_i: time preference dummies; and X_i: vector of the confounding variables for Y.

The dependent variable is the persistence of obesity in 2007 and 2014 (never obese, transiently obese, chronically obese), while the independent variables are the condition in either 2007 or 2014. Confounding variables for Y_i are age, marital status, number of household members, gender, education, physical intensity of work, wealth, urban/rural residency, access to drinking water and sanitation, smoking habits, BMI, and percentage of food expenditure. The coefficients are expressed in odds ratio. Table 3 provides descriptions for each variable used in this study.

Result and discussion

Descriptive statistics

Several datasets from each IFLS module containing each required variable were merged to create the final dataset of this study. Pregnant individuals were dropped from the sample. The final sample size for regression using variables from 2007 is 16,366 respondents while the sample size for regression using variables from 2014 is 21,534 respondents. For brevity, the following descriptive statistics only analyse the independent variables from 2007. However, the overall description is the same when using independent variables from 2014. The minimum age of the sample is 15 because the risk and time preference module was only administered to respondents aged 15 and over. BMI in 2014 in this study sample has an average of 23.87 kg/m2 and a standard deviation of 4.51 kg/m^2. Fourteen percent of 16,366 or 2,294 observations were obese in 2007. The number is higher than the rate of obesity from the Indonesian basic national health survey (Riset Kesehatan Dasar/Riskesdas), a general health survey conducted by the Indonesian Ministry of Health that stood at 10.5% in 2007 (Kementerian Kesehatan, 2018). The relatively high difference in the prevalence of obesity between the IFLS sample and Riskesdas might be due to the IFLS sample that is more skewed to the urban population.

Figure 1 depicts the distribution of the obesity status of our sample between 2007 and 2014. Most of the obese respondents in 2007 (83.3%) were still obese in 2014, or what is defined as chronic obesity. Thus, once obese, there is a high chance that someone will remain obese for the next 7 years. In the same period, 1,690 non-obese respondents in 2007 became obese in 2014 (transiently obese). Even though the not obese to obese rate is low (12% of 14,072 respondents), the number is quite large compared to the number of obese, increasing the obesity rate in 2014 to 22%. The rate is quite similar to the number from Riskesdas in 2018, which stood at 21.8%.

Table 4 shows the distribution of the categorical variable (row frequency) and the mean and standard deviation of the continuous variable by each obesity status; BMI/obesity data are collected from IFLS5 and IFLS4, while other variables are from IFLS4. The percentage of respondents who are uncertainty averse is 47.32%, which means that almost half of the sample respondents displayed an uncertainty aversion attitude. Compared to risk-tolerant respondents

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Table 3. Variable Description

	No.	Variable	Description
Obesity measure	**Dependent variable**		
	1	Obesity status	Ordinal variable valued 0 for never obese, 1 for transiently obese, and 2 for chronically obese
	Interest variables		
Individual preference	2	Risk preference	Two dummies for risk-tolerant individuals and uncertainty-averse (UA) individuals. Risk-averse individuals as the reference group
	3	Time preference	Dummy valued 1 for impatient individuals. Patient individuals as the reference group
	Confounding variables		
Demographic factors	4	Age	Dummy valued 1 for individuals aged the 30s, 40s, 50s, or 60 and older
	5	Gender	Dummy valued 1 for males and 0 for female
	6	Marital status	Dummy valued 1 for formally married
	7	Education	Dummy valued 1 for individuals that finished high school or university degrees
Physical intensity factors	8	Physical intensity of work	Dummy valued one based on the intensity (hard, medium, light, sedentary) with not working as the base
	9	Physical activity	The intensity of physical activity in 100 MET-minutes/week (metabolic equivalent of task). Calculated using guidelines made by the International Physical Guidelines for Data Processing and Activity Questionnaire (IPAQ, 2005)
Wealth and residency factors	10	Residency	Dummy valued 1 for urban and 0 for rural.
	11	Wealth	Log (sum of wealth per capita)
Food allocation factors	12	Percentage of food expenditure	Percentages of food expenditure per type of food (staple food, vegetables, high calorie/fat foods, and fish and meat)
Habit and sanitary factors	13	Smoking habit	Dummy valued 1 for having a smoking habit
	14	Access to clean water	Dummy valued 1 for having access to mineral water/pipe/well
	15	Toilet	Dummy valued 1 for having own toilet in the house

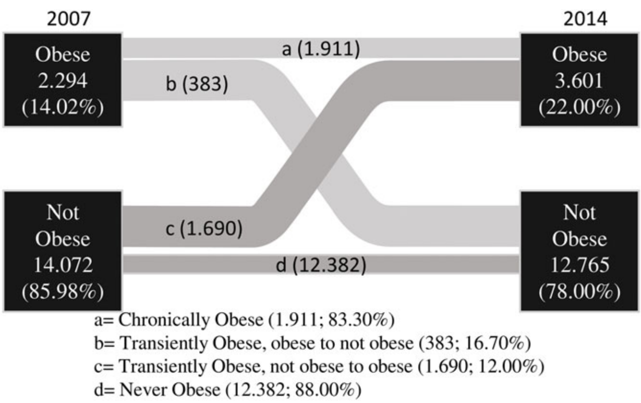

Figure 1. The Dynamicity of Obesity.

Table 4. Descriptive Statistics

		Never obese	Transiently obese	Chronically obese	Obs
	Observations	12,382	2,073	1,911	
Individual preference	**Categorical variables**				
	Risk-averse	76.55%	12.24%	11.21%	5,476
	Risk-tolerant	76.50%	12.31%	11.19%	3,145
	Uncertainty-averse	74.68%	13.12%	12.20%	7,745
	Patient	78.06%	10.54%	11.40%	702
	Impatient	75.55%	12.76%	11.69%	15,664
Demographic factors	Not married	78.06%	10.54%	11.40%	702
	Married	75.55%	12.76%	11.69%	15,664
	Age 20s	84.16%	11.20%	4.64%	2,929
	Age 30s	73.80%	12.99%	13.21%	13,437
	Age 40s	73.39%	12.29%	14.32%	10,604
	Age 50s	79.83%	13.36%	6.80%	5,762
	Age 60 plus	77.29%	11.92%	10.79%	12,035
	Female	71.12%	14.73%	14.15%	4,331
	Male	77.11%	12.69%	10.19%	13,157
	Junior high school and below	77.19%	11.69%	11.13%	10,318
	Senior high school	74.62%	14.05%	11.33%	4,599
	University	68.05%	15.25%	16.70%	1,449
Physical intensity factors	Not working	72.87%	14.43%	12.70%	4,463
	Hard work	81.34%	10.19%	8.47%	3,092
	Medium work	80.07%	10.20%	9.73%	3,627
	Light work	73.65%	13.59%	12.76%	3,510
	Sedentary work	67.26%	15.95%	16.79%	1,674
Wealth and residency factors	Rural	80.23%	10.61%	9.16%	8,300
	Urban	70.95%	14.78%	14.27%	8,066
Habit and sanitary factors	Do not have a smoking habit	69.72%	15.73%	14.55%	10,402
	Have a smoking habit	86.02%	7.33%	6.66%	5,964
	Do not have clean water access	82.19%	9.37%	8.44%	1,836
	Have clean water access	74.83%	13.08%	12.09%	14,530
	Do not have a toilet in the house	80.73%	10.85%	8.43%	4,047
	Have a toilet in the house	73.99%	13.26%	12.74%	12,319
	Continuous variables				
Demographic	Family size	4.63	4.62	4.60	
factors		(1.83)	(1.79)	(1.72)	

(*Continued*)

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Table 4. (*Continued*)

		Never obese	Transiently obese	Chronically obese	Obs
Wealth and residency factors	Log(Wealth)	15.79	16.02	16.17	
		(1.76)	(1.62)	(1.87)	
Physical intensity factors	MET	37.73	29.44	27.86	
		(49.01)	(41.14)	(38.45)	
Food allocation factors	Share of staple food	0.23	0.20	0.20	
		(0.15)	(0.14)	(0.14)	
	Share of vegetables	0.09	0.09	0.09	
		(0.07)	(0.06)	(0.07)	
	Share of fish and meat	0.19	0.19	0.20	
		(0.10)	(0.10)	(0.11)	
	Share of high fat food	0.14	0.15	0.15	
		(0.12)	(0.13)	(0.12)	

Source: IFLS5 and IFLS4, processed; variables in this table represent the conditions in 2007; standard deviations for continuous variables in parentheses.

(19.22%), there are more risk-averse respondents (33.46%). The percentage of impatient respondents is 95.71%, while the percentage of patient respondents is only 4.29%.

For demographic factors, among different age groups, the chronic obesity rate was the highest in the age group 40–49 (more than 14%), and 81% of chronically obese individuals were aged between 20 and 49 years old, which is the most productive age. Married individuals contribute to almost 93% of chronically obese individuals. Thus, the stylised facts seem consistent with the previous studies on factors that contribute to obesity in Indonesia (Pengpid and Peltzer, 2017).

Table 4 shows that the chronic obesity rate is higher among respondents who are uncertainty averse (12.20%) than among risk-averse and risk-tolerant respondents (11.21% and 11.19%). The percentage of never obese is higher for patient respondents (78.06%) than impatient respondents (75.55%). The percentage of impatient respondents is slightly higher among chronically obese respondents (95.81%) than never obese respondents (95.57%).

Regression analysis

The interest variables' robustness was tested by regression with and without confounding variables based on several categories: demographic, lifestyle, and knowledge factors. Nevertheless, the interpretation of the results is based on the estimation with control variables. Table 5 shows the results using the ordered logit estimation mentioned above for estimates with and without control variables. As previously discussed, we display both regression results using independent variables in 2007 and 2014.

The estimates presented in Table 5 are in odds ratio. We show both regressions without control variables (column (1) and (3)) and with control variables (column (2) and (4)). For brevity, we only interpret the results with control variables in the following sentences. Using 2007 independent variables, all preference variables are statistically significant. Risk-tolerant and uncertainty-averse individuals are more likely to experience obesity than risk-averse individuals. Similarly, impatient respondents are more likely to be transiently or chronically obese. Being impatient is associated with a 23.3% increase in the likelihood of being transiently or chronically

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Table 5. Ordered Logit Estimation Result (Odds Ratio)

		Predictors in 2007				Predictors in 2014			
		(1)		(2)		(3)		(4)	
		OR [95% C]	*p*-value	OR [95% C]	*p*-value	OR [95% C]	*p*-value	OR [95% C]	*p*-value
Individual preference	Risk-tolerant	1.075	0.175	1.126**	0.034	0.959	0.326	0.978	0.616
		[0.968,1.195]		[1.009,1.257]		[0.883,1.042]		[0.896,1.067]	
	Uncertainty-averse	1.127***	0.004	1.126***	0.007	1.057	0.148	1.094**	0.028
		[1.038,1.224]		[1.032,1.228]		[0.980,1.140]		[1.010,1.186]	
	Impatient	1.167	0.104	1.233**	0.033	1.311***	0.001	1.160*	0.072
		[0.969,1.404]		[1.017,1.495]		[1.123,1.531]		[0.987,1.364]	
Demographic factors	Married			1.701***	0.000			1.719***	0.000
				[1.506,1.920]				[1.557,1.899]	
	Age 30s			1.497***	0.000			2.043***	0.000
				[1.352,1.659]				[1.825,2.287]	
	Age 40s			1.694***	0.000			2.953***	0.000
				[1.513,1.896]				[2.631,3.315]	
	Age 50s			1.252***	0.001			3.047***	0.000
				[1.093,1.436]				[2.680,3.464]	
	Age 60 plus			0.554***	0.000			1.778***	0.000
				[0.446,0.687]				[1.530,2.066]	
	Male			0.507***	0.000			0.538***	0.000
				[0.453,0.567]				[0.486,0.597]	
	Family size			0.996	0.754			0.991	0.387
				[0.974,1.019]				[0.970,1.012]	
	Senior high school			1.031	0.527			1.012	0.789
				[0.937,1.135]				[0.928,1.103]	
	University			1.168**	0.037			1.168**	0.011
				[1.010,1.351]				[1.037,1.317]	

(*Continued*)

Table 5. (*Continued*)

		Predictors in 2007				Predictors in 2014			
		(1)		(2)		(3)		(4)	
		OR [95% C]	*p*-value	OR [95% C]	*p*-value	OR [95% C]	*p*-value	OR [95% C]	*p*-value
Physical intensity factors	Hard work			0.974	0.691			0.912*	0.080
				[0.856,1.108]				[0.822,1.011]	
	Medium work			1.001	0.992			0.920	0.160
				[0.888,1.127]				[0.820,1.033]	
	Light work			1.150**	0.011			0.910*	0.077
				[1.032,1.281]				[0.819,1.010]	
	Sedentary work			1.234***	0.002			1.068	0.253
				[1.081,1.410]				[0.954,1.195]	
	MET			0.998***	0.001			0.998***	0.000
				[0.997,0.999]				[0.997,0.999]	
Wealth and residency factors	Urban			1.350***	0.000			1.351***	0.000
				[1.233,1.479]				[1.240,1.471]	
	Log(Wealth)			1.076***	0.000			1.067***	0.000
				[1.044,1.108]				[1.042,1.092]	
Food allocation factors	Share of staple food			0.520***	0.000			0.647***	0.007
				[0.361,0.748]				[0.472,0.887]	
	Share of vegetables			0.550*	0.064			1.807**	0.038
				[0.292,1.035]				[1.034,3.160]	
	Share of fish and meat			1.723**	0.015			1.631**	0.013
				[1.110,2.676]				[1.110,2.397]	
	Share of high fat food			1.116	0.581			1.304*	0.077
				[0.755,1.650]				[0.972,1.751]	

(*Continued*)

Table 5. (*Continued*)

		Predictors in 2007				Predictors in 2014			
		(1)		(2)		(3)		(4)	
		OR [95% C]	*p*-value	OR [95% C]	*p*-value	OR [95% C]	*p*-value	OR [95% C]	*p*-value
Habit and sanitary factors	Smoking habit			0.638***	0.000			0.658***	0.000
				[0.563,0.724]				[0.586,0.739]	
	Water access			1.180**	0.025			1.291***	0.000
				[1.021,1.364]				[1.123,1.483]	
	Toilet			1.126**	0.026			1.088	0.137
				[1.015,1.250]				[0.974,1.215]	
	N	16366		16366		21534		21534	

Note: This table shows the exponentiated coefficients, 95% confidence intervals (CI) in brackets, and *p*-value in the second column of each regression. Columns (1) and (3) show coefficients for regression without control variables, while columns (2) and (4) show coefficients for regression with control variables. Standard errors are clustered at the household level; ***$p < 0.01$; **$p < 0.05$.

obese. The uncertainty-averse individuals are 12.6% more likely to experience obesity. Risk tolerance is associated with an increase in the likelihood of being obese by 12.6%. However, using the 2014 independent variables, only the uncertainty aversion variable has a significant coefficient with a 9.4% increase in the likelihood of being obese.

For the other factors, the regression results using 2007 or 2014 independent variables yield relatively similar coefficients in terms of significance and direction, with only a slight difference. The overall results imply the following: Among demographic factors, married individuals are more likely to be obese than single individuals. Compared to individuals aged 20–29, older individuals tend to be more obese. Females also are more likely to be obese than males. A university degree also increases the probability of being obese compared to those who only have a junior high school degree or below. Living in an urban region and having more wealth also increase the propensity to be obese. Households with a higher share of their food budget on staple food are less likely to be obese. In contrast, higher fish and meat allocation leads to obesity. Smokers are less likely to be obese. Access to clean water increases the probability of being obese. The differences between the 2007 and 2014 results are as follows: Compared to the 2007 results, work intensity and having a toilet in 2014 do not predict obesity. Additionally, while negatively correlated in 2007, the share of vegetables and individuals aged above 60 in 2014 show a positive correlation with obesity.

Discussion

Of all the risk and time preference variables, uncertainty aversion is the most consistent predictor with statistical significance (*p*-value below 5%) in every estimation. This evidence suggests that the reluctance to face uncertainty might play an essential role in the increasing trend of obesity, and interventions for obesity should consider the unwillingness of individuals to change their behaviour from the status quo. Economic preferences for risk-taking or risk-aversion are influenced by financial conditions, where wealthier individuals are more willing and able to take risks (Dohmen *et al.*, 2011). Additionally, chronic stress has been linked to increased risk-taking behaviour in adults (Ceccato *et al.*, 2016). Emotions also significantly drive many important life decisions (Lerner *et al.*, 2015). It highlights that financial conditions and stress significantly shape risk-taking behaviour, which could lead to obesity. Thus, the socioeconomic and biological factors associated with risk-taking behaviour and obesity should be considered in discussions on obesity. In other studies, de Oliveira *et al.* (2016) found that more risk-tolerant individuals are more likely to have a higher BMI. Similarly, Sutter *et al.* (2013) found that more risk-averse individuals have a lower BMI. However, Dogbe and Gil (2019) found that BMI was significantly and positively associated with risk aversion.

As for time preference, an impatient attitude increases one's tendency to be obese. These results are in line with studies that found a positive relationship between the discount rate and obesity (Brown and Biosca, 2016; Chabris *et al.*, 2008; de Oliveira *et al.*, 2016; Dogbe and Gil, 2019; Smith *et al.*, 2005; Sutter *et al.*, 2013; Richards and Hamilton, 2012). The results of this study enriched the evidence that directly elicited economic preferences have power in explaining obesity. This study also proved that the elicitation of these preferences, although relatively simple compared to the experimental method, can still predict obesity incidence in a nationally representative sample. Nevertheless, the results for risk tolerance and time preference should be interpreted with caution as they can only predict obesity using past behaviour (2007) but not using current behaviour (2014).

With much evidence that obesity and the discount rate are positively correlated, public policy to overcome obesity must begin to consider that individuals with higher discount rates are more likely to become obese. Richards and Hamilton (2012) argued that taxing foods will not be effective. However, taxes raise current prices and reduce current consumption to increase

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consumers' expectations of future prices. Consumers with low discount rates will significantly reduce current consumption because they value future consumption. Simultaneously, consumers with high discount rates will keep their current consumption the same because they give a lower weight to future costs and benefits. Richards and Hamilton (2012) suggested that policies to tackle obesity are carried out by providing information to the public about the long-term effects of consuming excess calories rather than directly taxing foods that are considered unhealthy. Providing discounted insurance premiums for individuals that show an increase in healthy activities and accelerate the benefits of healthy activities can also help individuals prevent and reduce obesity. Charness and Gneezy (2009) found that incentivising individuals to exercise increases physical activity and health conditions. The unwillingness of individuals to change their behaviour from the status quo, that is, having a high-calorie consumption and low level of physical activity, could be alleviated by improving the quality of the built environment around the cities of Indonesia.

Besides the influence of risk and time preferences on obesity, demographic and lifestyle factors also play a role in influencing obesity, such as being female, being married, having a university degree, having light and sedentary work, having higher spending allocation on fish and meat, having more wealth, having more sanitary access, and living in urban areas. Generally, highly educated, high-income, and urban-centric individuals are more likely to be obese in Indonesia; this is in line with the findings from Pengpid and Peltzer (2017). Social and environmental factors play a crucial role in obesity. This study aligns with numerous others in finding that obesity is linked to factors such as sex, race, ethnicity, and socioeconomic status. The prevalence of obesity can also be influenced by factors such as food availability, sedentary lifestyles, and access to low-nutrient food options.

Food allocation also plays a role in predicting obesity. Rice is the staple food in Indonesia, with other popular starchy foods such as noodles, corn, sago, cassava, and sweet potatoes also being consumed. Although these staple foods are high in calories, which would be expected to positively correlate with obesity, households with high staple food expenditure often do not have the means to afford a diverse range of foods. Rice/grain expenditure has a direct impact on malnutrition and dietary diversity. Increased rice expenditure has been positively correlated with the percentage of underweight children, while declining rice expenditure leads to increased spending on non-rice foods, resulting in a more diverse and nutritious diet and a decrease in the percentage of underweight children (Thorne-Lyman *et al.*, 2010; Torlesse *et al.*, 2003). In Indonesia, the highest rates of obesity are found in Java and Bali, the most developed islands. The occurrence of obesity varied greatly depending on geography and socioeconomic status, with the highest rates being seen in urban areas and among the most affluent and educated groups (Ayuningtyas *et al.*, 2022).

Even though individuals with higher socioeconomic status are more likely to become health-conscious (Prentice, 2006; Ziraba *et al.*, 2009), the low quality and lack of public facilities in developing countries would hurt the effort to reduce obesity prevalence among them. Leather *et al.* (2011) pointed out the need to improve the walking environments in many Asian cities, including Indonesia. The provision of walking paths and pedestrian facilities needs more attention to fulfil pedestrian needs and increase daily physical activity.

While individual choice may play a role in obesity, it cannot be viewed in isolation. This study highlights the influence of preference on obesity prevalence and the importance of considering socioeconomic context when examining this issue. Information on the risks of obesity and calorie intake, incentives to prevent obesity, and improvements to the built environment, such as public parks, transportation, and walkways, can help to address the rising prevalence of obesity. It highlights the need for a holistic approach to tackling obesity, one that considers both individual choices and broader societal factors.

Conclusion

This study estimated the relationship between individual risk and time preference and obesity. The persistence of obesity was measured by constructing transient and chronic obesity. Using the 2007 independent variables, the results show that impatient individuals are more likely to be both transiently and chronically obese than patient individuals, and risk tolerance and uncertainty aversion also increase the probability of being transiently and chronically obese. However, using the 2014 independent variables, only uncertainty aversion is statistically significant in predicting an increase in obesity. This indicates that the current behaviour of risk tolerance and time preference is not associated with obesity, while past behaviours are associated with obesity.

This study suggests that risk and time preference might play an essential role in determining individual unhealthy behaviours, especially in excessive calorie consumption, which ultimately leads to obesity. Therefore, policies tackling obesity problems should consider the role of risk and time preference in their formulation.

Also, individuals with higher socioeconomic status are more likely to be either transiently or chronically obese. Nevertheless, they need access to leisure sports and public facilities to increase their physical activity. Therefore, improving the quality of the built environment, such as public parks, public transportation, and footpath as public facilities for people to be able to do vigorous leisure activities, is needed to encourage the increase in physical activity, thus lowering the prevalence of obesity.

Limitation and recommendation

The study could not use other obesity measurements other than BMI because waist circumference and WHR are only recorded for respondents over the age of 40. If there is other available data, estimates using different obesity measurements might be helpful for robustness check if the sample is the same. Besides risk aversion and discount rate, there are other concepts of risk and time preference, such as probability weighting, as in de Oliveira *et al.* (2016), and time inconsistency, as in Richards and Hamilton (2012), that might explain more about the behaviour of calories consumption. However, applying the national scale survey concept might take too much time and resources.

Data availability statement. The dataset supporting the conclusions of this article is available in the RAND IFLS website: https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html.

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Ethical standard. We use the IFLS survey data that IRBs have approved. Please refer to the link for more detailed information regarding the ethical approval. https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html

References

Abe R, and Kato H (2014). Effect of built environment on gasoline consumption in a developing megacity: evidence from the Jakarta, Indonesia, metropolitan area. *Transportation Research Record* **2454**, 12–19. https://doi.org/10.3141/2454-02

Aizawa T, and Helble M (2017). Socioeconomic inequality in excessive body weight in Indonesia. *Economics and Human Biology* **27**, 315–327. https://doi.org/10.1016/j.ehb.2017.09.005

Anandari A, and Nuryakin C (2019). The effect of risk preference on choice between public and private sector employment in Indonesia. *International Journal of Business and Society* **20**(S1), 177–196.

Ayuningtyas D, Kusuma D, Amir V, Tjandrarini DH, and Andarwati P (2022). Disparities in obesity rates among adults: analysis of 514 districts in Indonesia. *Nutrients* **14**, 1–18. https://doi.org/10.3390/nu14163332

Bhurosy T, and Jeewon R (2014). Overweight and obesity epidemic in developing countries: a problem with diet, physical activity, or socioeconomic status? Scientific World Journal 2014. https://doi.org/10.1155/2014/964236

Brown H, and Biosca O (2016). Exploring the relationship between time preference, body fatness, and educational attainment. *Social Science and Medicine* **158**, 75–85. https://doi.org/10.1016/j.socscimed.2016.04.016

Burkhauser RV, and Cawley J (2008). Beyond BMI: the value of more accurate measures of fatness and obesity in social science research. *Journal of Health Economics* **27**, 519–529. https://doi.org/10.1016/j.jhealeco.2007.05.005

Cao HH, Han B, Zhang HH, and Hirshleifer DA (2011). Fear of the unknown: familiarity and economic decisions. *SSRN Electronic Journal* **January**. https://doi.org/10.2139/ssrn.985381

Ceccato S, Kudielka BM, and Schwieren C (2016). Increased risk taking in relation to chronic stress in adults. *Frontiers in Psychology* **6**, 1–13. https://doi.org/10.3389/fpsyg.2015.02036

Chabris CF, Laibson D, Morris CL, Schuldt JP, and Taubinsky D (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of Risk and Uncertainty* **37**, 237–269. https://doi.org/10.1007/s11166-008-9053-x

Charness G, and Gneezy U (2009). Incentives to exercise. *Econometrica* **77**, 909–931. https://doi.org/10.3982/ecta7416

Chowdhury S (2016). An Alternative View on Smoking Compulsion in Indonesia: The Effects of Myopia and Risk. Dissertation, University of Warwick.

de Oliveira ACM, Leonard TCM, Shuval K, Skinner CS, Eckel C, and Murdoch JC (2016). Economic preferences and obesity among a low-income African American community. *Journal of Economic Behavior and Organization* **131**, 196–208. https://doi.org/10.1016/j.jebo.2015.11.002

Dinsa GD, Goryakin Y, Fumagalli E, and Suhrcke M (2012). Obesity and socioeconomic status in developing countries: a systematic review. *Obesity Reviews* **13**, 1067–1079. https://doi.org/10.1111/j.1467-789X.2012.01017.x

Diza F, Nuryakin C, and Muchtar PA (2022). Parent's risk preference and childhood vaccination: evidence from Indonesia. *Journal of Public Health Policy* **43**, 659–669. https://doi.org/10.1057/s41271-022-00375-5

Dogbe W, and Gil JM (2019). Linking risk attitudes, time preferences, and body mass index in Catalonia. *Economics and Human Biology* **35**, 73–81. https://doi.org/10.1016/j.ehb.2019.05.005

Dohmen T, Falk A, Huffman D, Sunde U, Schupp J, and Wagner GG (2011). Individual risk attitudes: measurement, determinants, and behavioral consequences. *Journal of the European Economic Association* **9**, 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x

Frank LD, Andresen MA, and Schmid TL (2004). Obesity relationships with community design, physical activity, and time spent in cars. *American Journal of Preventive Medicine* **27**, 87–96. https://doi.org/10.1016/j.amepre.2004.04.011

Friedman M, and Savage L (1948). The utility analysis of choices involving risk. *The Journal of Political Economy* **56**, 279–304.

Gneezy U, List JA, and Wu G (2006). The uncertainty effect: when a risky prospect is valued less than its worst possible outcome. *The Quarterly Journal of Economics* **121**, 1283–1309. https://doi.org/10.1093/qje/121.4.1283

Ida T, and Goto R (2009). Simultaneous measurement of time and risk preferences: stated preference discrete choice modeling analysis depending on smoking behavior. *Behavioral Economics of Preferences, Choices, and Happiness* **50**, 27–48. https://doi.org/10.1007/978-4-431-55402-8_2

IPAQ (2005). Guidelines for data processing and analysis of the international physical activity questionnaire (IPAQ) – short and long forms. IPAQ, November, 1–15.

Kementerian Kesehatan (2018). Laporan Nasional Riskesdas 2018. Badan Penelitian dan Pengembangan Kesehatan, Kementerian Kesehatan RI.

Kim Y, and Radoias V (2016). Education, individual time preferences, and asymptomatic disease detection. *Social Science and Medicine* **150**, 15–22. https://doi.org/10.1016/j.socscimed.2015.11.051

Komlos J, Smith PK, and Bogin B (2004). Obesity and the rate of time preference: is there a connection? *Journal of Biosocial Science* **36**, 209–219. https://doi.org/10.1017/S0021932003006205

Leather J, Fabian H, Gota S, and Mejia A (2011). Walkability and pedestrian facilities in Asian cities state and issues. *Asian Development Bank Sustainable Development Working Paper Series* **17**, 69.

Lerner JS, Li Y, Valdesolo P, and Kassam KS (2015). Emotion and decision making. *Annual Review of Psychology* **66**, 799–823. https://doi.org/10.1146/annurev-psych-010213-115043

Mann S (2008). Framing obesity in economic theory and policy. *Review of Social Economy* **66**, 163–179. https://doi.org/10.1080/00346760701668461

Mustillo S, Worthman C, Erkanli A, Keeler G, Angold A, and Costello EJ (2003). Obesity and psychiatric disorder: developmental trajectories. *Pediatrics* **111**, 851–859. https://doi.org/10.1542/peds.111.4.851

Muzayanah IFU, Damayati A, Indraswari KD, Simanjuntak EM, and Arundina T (2022). Walking down the street: how does the built environment promote physical activity? A case study of Indonesian cities. *International Journal of Urban Sustainable Development* **14**, 425–440. https://doi.org/10.1080/19463138.2022.2135099

Ng JL (2013). Essays on the empirics of risk and time preferences in Indonesia. ProQuest Dissertations and Theses August, 142. http://search.proquest.com/docview/1458630515?accountid = 13771

Pampel FC (2012). Obesity, SES, and economic development: a test of the reversal hypothesis. *Social Science and Medicine* **74**, 1073–1081.

Papas MA, Alberg AJ, Ewing R, Helzlsouer KJ, Gary TL, and Klassen AC (2007). The built environment and obesity. *Epidemiologic Reviews* **29**, 129–143. https://doi.org/10.1093/epirev/mxm009

Pengpid S, and Peltzer K (2017). The prevalence of underweight, overweight/obesity and their related lifestyle factors in Indonesia, 2014–15. *AIMS Public Health* **4**, 633–649. https://doi.org/10.3934/publichealth.2017.6.633

Permani R (2011). Revisiting the link between maternal employment and school-aged children health status in developing countries: an instrumental variable approach. School of Economics and Public Policy Working Papers 2011-21, University of Adelaide, School of Economics and Public Policy.

Philipson TJ, and Posner RA (1999). Nber Working Paper Series the Long-Run Growth in Obesity As a Function of Technological Change. http://www.nber.org/papers/w7423

Prentice AM (2006). The emerging epidemic of obesity in developing countries. *International Journal of Epidemiology* **35**, 93–99. https://doi.org/10.1093/ije/dyi272

Richards TJ, and Hamilton SF (2012). Obesity and hyperbolic discounting: an experimental analysis. *Journal of Agricultural and Resource Economics* **37**, 181–198.

Ritchie H, and Roser M (2017). Obesity: Our World in Data. https://ourworldindata.org/obesity

Samuel F, and Atinmo T (2008). Obesity and cardiovascular diseases: the risk factor in African diets. *Forum on Public Policy: A Journal of the Oxford Round Table January 2008.*

Sanjaya M (2013). On the source of risk aversion in Indonesia using micro data 2007. Economics Discussion Paper No. 2013-33.

Smith PK, Bogin B, and Bishai D (2005). Are time preference and body mass index associated? Evidence from the national longitudinal survey of youth. *Economics and Human Biology* **3**(2 SPEC. ISS.), 259–270. https://doi.org/10.1016/j.ehb.2005.05.001

Sohn K (2016). Risk incomprehension and its economic consequences. *Journal of Development Studies* **52**, 1545–1560. https://doi.org/10.1080/00220388.2016.1166208

Sohn K (2017). The risk preferences of entrepreneurs in Indonesia. *Bulletin of Economic Research* **69**, 271–287. https://doi.org/10.1111/boer.12088

Sutter M, Kocher MG, Daniela GR, and Trautmann ST (2013). Impatience and uncertainty: experimental decisions predict adolescents' field behavior. *American Economic Review* **103**, 510–531. https://doi.org/10.1257/aer.103.1.510

Thorne-Lyman AL, Valpiani N, Sun K, Semba RD, Klotz CL, Kraemer K, Akhter N, De Pee S, Moench-Pfanner R, Sari M, and Bloem MW (2010). Household dietary diversity and food expenditures are closely linked in rural Bangladesh, increasing the risk of malnutrition due to the financial crisis. *Journal of Nutrition* **140**. https://doi.org/10.3945/jn.109.110809

Torlesse H, Kiess L, and Bloem MW (2003). Association of household rice expenditure with child nutritional status indicates a role for macroeconomic food policy in combating malnutrition. *Journal of Nutrition* **133**, 1320–1325. https://doi.org/10.1093/jn/133.5.1320

Turconi G, Guarcello M, Cignoli F, Setti S, Bazzano R, Roggi C, and Maccarini L (2008). Eating habits and behaviors, physical activity, nutritional and food safety knowledge and beliefs in an adolescent Italian population. *Journal of the American College of Nutrition* **27**, 31–43. https://doi.org/10.1080/07315724.2008.10719672

Wang Y, and Beydoun MA (2007). The obesity epidemic in the United States – gender, age, socioeconomic, racial/ethnic, and geographic characteristics: a systematic review and meta-regression analysis. *Epidemiologic Reviews* **29**, 6–28. https://doi.org/10.1093/epirev/mxm007

World Health Organization (2018). Obesity and Overweight: World Health Fact Sheet. https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

Ziraba AK, Fotso JC, and Ochako R (2009). Overweight and obesity in urban Africa: a problem of the rich or the poor? *BMC Public Health* **9**, 1–9. https://doi.org/10.1186/1471-2458-9-465

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