Macrothink Institute™

International Journal of Global Sustainability
ISSN 1937-7924
2024, Vol. 8, No. 1

Rural-urban Migration and Overweight Status in Low- and Middle-income Countries: Evidence from Longitudinal Data in Indonesia

Weilong Li

Population Studies Center & Department of Sociology

University of Pennsylvania, USA

Received: June 11, 2024 Accepted: July 15, 2024 Published: September 7, 2024

doi:10.5296/ijgs.v8i1.22239 URL: https://doi.org/10.5296/ijgs.v8i1.22239

Abstract

With rapid urbanization and intensive rural-urban migration, being overweight has become an increasingly common source of health risks in low- and middle-income countries (LMICs). However, the impact of rural-urban migration on overweight status is understudied in the LMIC context. Previous studies primarily used cross-sectional data, failing to adjust for migration health selection. Furthermore, the potential gender pattern in the impact of rural-urban migration remained unclear, and the potential cumulative effect of the duration of urban residence among migrants was rarely examined with longitudinal data. Meanwhile, the mediating effects of health behavioral factors were poorly understood. Using data from the fourth and fifth waves of the Indonesia Family Life Survey (IFLS) and employing fixed-effects (FE) models (N=7267), this study provided new evidence on the impact of rural-urban migration on overweight status across time and gender. Findings suggest that rural-urban migration significantly and positively predicted being overweight, and the association was significantly stronger among women than men. The results also show that years lived in urban areas did not significantly predict overweight among migrants, and that mediating health-related behaviors did little to explain adverse weight outcomes of migrants. As the number of rural-urban migrants continues growing, LMIC governments should implement health interventions aiming for healthy weight status among migrant communities. Meanwhile, gender-specific programs targeting women should be considered. Future research should explore other potential mediators of the link between rural-urban migration and overweight.

1. Introduction

The rising prevalence of overweight is a global health crisis, affecting 2.2 billion people worldwide (World Bank, 2020). However, research on the causes and consequences of overweight have focused overwhelmingly on high-income countries, with relatively less attention to the rest of the world. This is problematic because over 70% of the 2.2 billion overweight population reside in low- and middle-income countries (LMICs), and overweight has become a leading risk factor for morbidity and mortality in these countries (World Bank, 2020). Specifically, it is one of the most prominent risk factors of various non-communicable diseases (NCDs), such as cardiovascular diseases and cancer, and causes 2.8 million deaths annually, most of which take place in LMICs (World Health Organization, 2020). Increasing rates of overweight and related NCDs also severely constrain the socioeconomic development of LMICs by reducing productivity and life expectancy while increasing disability and health care costs (World Bank, 2020). The financial costs of overweight and obesity are projected to exceed $7 trillion among LMICs in the next 15 years (World Bank, 2020). Therefore, it is of paramount significance to understand the patterns and driving forces of overweight in LMICs, to improve the health and wellbeing of their populations and facilitate their social and economic development.

The rising health burden of overweight in LMICs is closely associated with the rapid urbanization process and the increase in urban populations. LMICs are projected to have the highest urbanization rates in the next few decades and the proportion of urban population is projected to reach 59% by 2050 (United Nations, 2018). Extensive rural- urban migration is one of the key driving forces of the fast urban population increase in LMCs (Brueckner & Lall, 2015; United Nations, 2018). It is estimated that the large-scale rural-urban migration, together with the natural increase of urban population, will add 2.5 billion people to cities by the middle of the century, 90% of whom will reside in LMICs (United Nations, 2018). The arrival of migrants from rural areas in cities not only gives them access to health-benefitting resources, such as clean water sources and quality health care services, but also exposes them to urban environments in which being overweight is more prevalent. With the continually increasing number of migrants arriving in cities from rural areas, it is critical to understand the impact of rural-urban migration on overweight in LMICs.

Still, existing research on overweight in LMICs focused more on socioeconomic status (SES) and demographic factors, finding a positive association among people in low-income countries as well as women in middle-income countries, with mixed results for men in middle-income countries (Dinsa et al., 2012). Compared with SES, relatively less attention was given to the impact of urban settings on overweight. Overall, existing research consistently documented that urban residence was associated with higher chances of being overweight in LMICs (Dinsa et al., 2012; Neuman et al., 2013; Mayen et al., 2014). Most of these studies draw comparisons between people with urban and rural residence, ignoring the potentially unique experience of rural-urban migrants by mixing them with urban residents. Rural-urban migrants share similar living habits with rural dwellers before migration and are exposed to the same urban settings as urban residents after migration. Therefore, they may differ from rural/urban non-migrants in overweight status and should be considered as a separate group in the analysis.

Researchers have recently started to pay more attention to rural-urban migrants and showed inconclusive patterns of the association between rural-urban migration and overweight in different LMICs. In India, some researchers reported an obesity gradient, with urban residents having the highest prevalence, rural dwellers the lowest, and rural- urban migrants in between (Ebrahim et al., 2010), while others found that the significantly higher odds of being overweight/obese among rural-urban migrants than rural dwellers was only observed among women (Varadharajan et al., 2013). In China, rural-urban migrants had a similar risk of being overweight with urban residents, which was significantly higher than that of rural dwellers (Li, 2022). A similar pattern was also observed in Peru (Creber et al., 2010). Another study in China compared rural-urban migrants with rural dwellers of the same minority ethnic group within a province, and showed that migrants were more than twice as likely to be overweight and obese than rural dwellers (Wang et al., 2021). The associations between rural-urban migration and overweight status were also mixed in the least developed countries in sub-Saharan Africa (SSA). For instance, rural-urban migration significantly predicted overweight and obesity in Malawi (Chilunga et al., 2019), whereas had no significant impact on overweight in Tanzania (Cockx et al., 2017) and Kenya (Peters et al., 2019).

Although previous studies have documented important links between rural-urban migration and being overweight, gaps in the literature remain. First and foremost, existing research largely relied on cross-sectional data and failed to adjust for the selection bias of migration. More specifically, moving from the countryside to cities is not a behavior that is randomly adopted. It is closely related to people's health status, as individuals who migrate normally have better health than those who remain. The migration health selection has been documented in many LMICs, such as China (Lu & Qin, 2014), Indonesia (Lu, 2008), Thailand (Nauman et al., 2015), and Malawi (Anglewicz et al., 2018). Cross-sectional data do not provide information on the health of rural-urban migrants before migration, and thus researchers cannot distinguish whether the observed differences between migrants and rural/urban non-migrants are indeed contributed by rural-urban migration or due to migrant selectivity. Likewise, with cross- sectional data, unobserved factors associated with both migration and health could confound the relationship between the two and may cause spurious associations. Therefore, it is preferrable to use longitudinal data to more accurately examine the impact of migration on health.

Second, many previous studies compared rural-urban migrants with populations at destinations, i.e., urban residents. This comparison might conflate and overstate the negative impact of rural-urban migration while neglecting its potential benefits on health because of the socioeconomic and health disparities between sending and receiving areas (Benatar, 1998; Lu, 2010). A more appropriate approach is to compare individuals' health with and without migration, which can be approximated by comparing the health of rural-urban migrants with similar non-migrants in rural areas (Lu, 2010), especially when longitudinal data can be leveraged to account for selection into migration.

Third, while there are important gender differences in the prevalence of being overweight (e.g., Ebrahim et al., 2010; Varadharajan et al., 2013; Chilunga et al., 2019), it is unclear whether the impact of rural-urban migration on overweight also differs by gender. The gender pattern is important because women are more vulnerable to chronic conditions related to being overweight but are less likely to be diagnosed and treated than men in LMICs (Bonita & Beaglehole, 2014). As women constitute an increasing sharing of rural-urban migrants in many LMICs, it is worth investigating if their health is impacted differently by migration from men.

Fourth, research on how migrants' duration of urban residence impacts overweight is scarce in LMICs. Many researchers did not include this variable in analyses due to data limitations, and a few studies that examined the length of migrants' urban life exposure showed inconsistent results (Chilunga et al., 2019; Peters et al., 2019; Li, 2022; Wang et al., 2021). The reliance on cross-sectional data in these studies is another important limitation.

Finally, pathways through which urban settings shape overweight status are puzzling. The mediating effects of health-related behaviors, especially changes in diets and physical activity, have rarely been analyzed with longitudinal data. Some research showed that moving to urban areas was followed by more sedentary lifestyles with higher rates of smoking and alcohol consumption (e.g. Ebrahim et al., 2010; Chilunga et al., 2019). However, data on the subject is not commonly available, and even when it is, the extent to which these health-related behaviors mediate the link between migration and weight is rarely examined. Nevertheless, understanding the mechanisms through which urban settings shape weight would contribute to more effective policy-making to curb the rising trend of overweight in LMICs.

Driven by these gaps, this study aimed to provide new evidence on rural-urban migration and overweight status by drawing longitudinal data from the fourth and fifth waves of the Indonesia Family Life Survey (IFLS) and using fixed-effects (FE) models to adjust for migrant selectivity and unobserved time-invariant confounders at both individual and wave levels. Indonesia faces a high prevalence of overweight and has huge flows of rural-urban migrants, among whom women account for a considerable proportion, offering an appropriate context to explore how rural-urban migration shapes overweight by gender in addition to both sexes combined. I also used the number of years lived in urban areas to predict overweight among migrants and examined the mediating effects of health-related behaviors. The findings will help LMIC governments better understand how the association between rural-urban migration and overweight varies across time and gender as well as its mediators, and implement more targeted and efficacious intervention programs to limit rising overweight.

2. Study Context

Indonesia is the fourth most populous country in the world and has had one of the highest urbanization rates in the world during the past few decades (United Nations, 2018); its urban population almost quadrupled from 32.8 million to 118.3 million between 1980 and 2010 (Mardiansjah et al., 2021). Fueled by extensive rural-urban migration, the Indonesian Central Bureau of Statistics estimated that the number of people residing in urban areas would increase by 3 million annually, and the urban population would reach 203 million by 2035, accounting for two-thirds of the Indonesian population (Mardiansjah et al., 2021). Meanwhile, the number of overweight adults has doubled during the past two decades, with prevalence rates increasing rapidly across all sociodemographic groups (World Health Organization, 2021). However, a thorough review revealed relatively little research on overweight and obesity in Indonesia (Rachmi et al., 2017). The dramatic increase in the urban population, the rising health burden of overweight, and the insufficient research on this issue all together make Indonesia a particularly appropriate context to study the impact of rural-urban migration on overweight in LMICs.

Another aspect that makes Indonesia an opportune setting for this analysis is the feminization of internal migration. Similar to many LMICs, the absolute number of men outweighs that of women among Indonesian internal migrants. However, the proportions of migrant women are higher in the age groups of 15-24 and 60 and above, and among married migrants (Sukamdi, 2015). The ample representation of migrant women in various sociodemographic categories in Indonesia provides an interesting context to explore the potential gendered impacts of urban residence on overweight status.

3. Data and Measures

Data for this study were drawn from the fourth and fifth waves of the Indonesian Family Life Survey (IFLS). The IFLS is an ongoing longitudinal socioeconomic and health survey in Indonesia. It is based on a sample of households representing approximately 93% of the Indonesian population in 13 of the 27 provinces in 1993 when the first wave of data collection was conducted (Strauss et al., 2016). IFLS4 was fielded in late 2007 and early 2008 with the same households and their split-offs from the first wave, and IFLS5 was conducted in late 2014 and early 2015 with the same set of households and their split-offs interviewed in IFLS4 (Strauss et al., 2016). Both IFLS4 and IFLS5 provide detailed information on migration histories, health conditions, and sociodemographic characteristics at the individual level as well as economic status and consumption behaviors at the household level.

3.1 Analytical Sample

There were 8,212 respondents (from 4,982 households) consisting of rural-urban migrants and rural dwellers presented in both waves of data (merged using unique respondent and household numbers). Rural dwellers were defined as respondents who lived in rural areas in the previous wave, remained in rural areas in the last wave, and reported no movements between waves. Rural-urban migrants were people who lived in rural areas in the fourth wave and moved to urban areas before the fifth wave. The categorization of rural and urban areas was based on the assignment by the Indonesian Bureau of Statistics (BPS) for each wave. Among these, 346 individuals were not measured for weight and/or height, and 599 individuals had missing values in other covariates. These observations are dropped[1]. The size of the final analytical sample was 7,267 (from 4,500 households) (N=7,267).

3.2 Model Specification

The dependent variable was overweight status, which was defined as having Body Mass Index (BMI, $\frac{weight(kg)}{height(m)^2}$) of 23 or higher. This cutoff was adopted by the World Health

[1] Additional analyses show no significant differences between dropped cases and the analytical sample.

Organization for Asian body figures and had been shown to have the best sensitivity and specificity for risk-factor identification (World Health Organization Expert Consultation, 2004). It had been widely used in research on the overweight status of Asian populations (e.g., Zhou, 2002; Jih et al., 2014; Hsu et al., 2015). The IFLS measured respondents' height and weight in both the fourth and fifth waves. This variable was binary, with 1 for being overweight. There were two main independent variables of interest. The first one was respondents' residential status, which was used in the set of models comparing rural-urban migrants with rural dwellers. A dummy variable was generated to indicate respondents' residential status. It was 0 for rural dwellers in both waves. For rural-urban migrants, it was 0 in the fourth wave and 1 in the fifth wave. The second main independent variable was the number of years lived in urban areas, which was used in the models restricted to rural-urban migrants. It was calculated by adding up all the time that rural-urban migrants spent in urban areas. The IFLS recorded detailed information about respondents' migration history, documenting the types of destination and the length of stay for each movement between the fourth and the fifth wave. The types of destination included "Big cities", "Small towns", and "Villages". Considering the overall low socioeconomic development level in Indonesia, small towns were also coded as urban areas, as people who reside in small towns would have very different lifestyles and much more exposure to urban settings than those who lived in rural villages. A robustness check showed that excluding "Small towns" from urban areas when calculating the duration of urban residence did not impact analysis results. For respondents who moved back and forth between rural and urban areas, only the time lived in urban areas was counted. For the fifth wave, the maximum value was 8 for migrants who moved to cities right after the previous wave in 2007 and stayed in the same urban areas in the last wave in 2015. The minimum value was 0 for respondents who just moved to urban areas in the same year in which the fifth wave of the survey was conducted. For the fourth wave, the variable was coded as 0 for all migrants because the focus of this paper was migration between the fourth and fifth waves.

This analysis also included a number of sociodemographic and health controls, including age, gender, marital status, education, household per capita income, self-rated physical health, and depression. Education was coded as a dummy variable because of the generally low education level in the sample, with 0 for "Primary school or below" and 1 for "Secondary school or above". Household income consisted of both salary/wage at the individual level as well as farm business profit, non-farm business profit, and non- labor income at the household level. The household income in the fourth wave was adjusted for inflation by using the World Bank's Consumer Price Index (CPI) ratio for Indonesia in 2007 and 2014. The household income per capita was obtained by using household income divided by the number of household members. Self-reported physical health was a binary variable where 1 indicated "Healthy or somewhat healthy" and 0 indicated "Unhealthy or somewhat unhealthy". Whether a respondent was depressed was included as a psychological factor. Both waves of the IFLS include 10 questions from the Center for Epidemiological Study of Depression Scale (CES-D), a widely-used screening tool for depression. Each question was scaled from 0 to 3, and a total score greater than or equal to 10 indicated depressive feelings (Andresen et al., 1994).

In addition, this study also included health behavioral factors: tobacco use, physical activity in the past week, and household per capita consumption of sugar and oil. They were associated with both urban lifestyles and weight changes. The IFLS asked respondents' current and history of smoking. A categorical variable was generated indicating whether a respondent was a current smoker, ever smoker, or never smoker. Physical activity was measured by whether respondents walked with moderate effort for more than 10 minutes during the past week. In terms of dietary patterns, the IFLS collected information on the amount of cooking oil (in liters) and sugar (in kgs) that a household last purchased in the past month. Monthly consumption provided a smoother estimate of diet than weekly expenditure data. Based on household size, I calculated per capita expenditures on oil and sugar, which were modeled as continuous.

4. Methods

I ran two sets of FE models with individual and wave FE to adjust for potential selection into migration and omitted variable bias (Allison, 2005). Adding individual FE essentially compared each individual at the fifth wave with him/herself at the fourth wave, and thus ruled out the impact of time-invariant factors, both observed and unobserved, at the individual level. Similarly, including wave FE in the models accounted for the fixed factors at the aggregate societal level between the two waves of the survey that were not captured in the data but might also affect people's migration decisions and overweight status.

The two most common FE models for estimating binary outcomes are conditional logit and linear probability models. The selection between the two models has been the subject of considerable debate in recent years, with advantages and disadvantages associated with each (e.g., Beck, 2020; Timoneda, 2021). The conditional logit model took into account the binary structure of the dependent variable but only keeps observations that had variation in the dependent variable across waves, dropping those that do not. In this study, only about 20% of the sample changed their overweight status across waves. Dropping those cases would not only dramatically reduce the analytic sample (and potentially introduce selection bias), but would also undermine the validity of point estimates because individuals with no changes in overweight status provide variations that could help identify parameters. Research showed that linear probability specification with fixed effects produced more accurate estimates and predicted probabilities than the logistic specification when less than 25% of the sample had variations in outcomes (Timoneda, 2021). Conditional logit models had additional disadvantages relating to the interpretation, especially when generating predicted probabilities at the lower end of the distribution of independent variables (Achen, 1982; Timoneda, 2021).

For these reasons, I estimated a linear probability model, which was superior in that it used information from all observations in the sample and provides coefficients that were easier to interpret. One potential disadvantage of linear probability models was that they may produce predicted probabilities that were out of the range of 0 and 1. However, the study aimed to assess the effect of rural-urban migration on overweight rather than predicting each individual's probability of being overweight. As such, the out-of-range predicted probabilities could be simply understood as close to 0 or 1. I also calculated predicted probabilities for observations in all models presented below and none had out- of-range predictions. Another disadvantage was that linear probability models violated the assumption of heteroscedasticity. To address this issue, I estimated robust standard errors clustered by households.

As a robustness check, I estimated logistic and linear specifications with the same dependent variable and independent variables, and found that they produce very similar average marginal effects (AME) (results are presented in the Appendix). Therefore, treating the binary outcome as linear would not affect the accuracy and efficiency of point estimates in this analysis. Moreover, since examining the mediating effects of health-behavioral factors was one of the research goals, linear probability models provided a much simpler and more straightforward way of comparing nested models by allowing us to compare coefficients directly.

The first set of models pooled rural-urban migrants and rural dwellers together and examined the impact of rural-urban migration on overweight status. The second set was limited to rural-urban migrants with years lived in cities being the main independent variable. Both sets of models made comparisons not only for the pooled sample of both sexes combined but also for each gender separately. The two sets of models are elaborated in the equations below.

$$\mathrm{overweight}_{it} = \beta_1 \mathrm{Residential\_status}_{it} + \Sigma_{k=2}^{10} \beta_k (\mathrm{control}_{kit}) + \alpha_i + y_t + u_{it} \quad (1)$$

$$\mathrm{overweight}_{it} = \beta_1 \mathrm{years\_in\_cities}_{it} + \Sigma_{k=2}^{10} \beta_k (\mathrm{control}_{kit}) + \alpha_i + y_t + u_{it} \quad (2)$$

In the first set of models, the independent variable of interest was the residential status for respondent *i* at time *t*, which was coded as 0 for all respondents in the previous wave and 1 for rural-urban migrants in the latest wave, and 0 was the reference group. In the second set of models, the key independent variable was the number of years lived in urban areas, which was 0 for all migrants in the previous wave. In both sets of models, the control variables included marital status, educational attainment, household income per capita, self-rated health, depression status, physical activity, tobacco use, and the household per capita consumption of cooking oil and sugar. The term α_i represented time-invariant individual effects, which controlled for sex, age, and all other fixed characteristics. The term y_t represented wave fixed effects, which controlled for unobserved fixed factors at the aggregate societal level between the two waves of surveys. Robust standard errors clustered by household were used to account for potential correlations among individuals within each household.

5. Results

5.1 Descriptive Statistics

Sample descriptive statistics are shown in Table 1 by migration status and survey year. There were 681 rural-urban migrants, accounting for 9.4% of the sample. They spent on average 3.6 years in urban areas between the two survey waves. The number of rural dwellers was 6,586.

While internal migration in Indonesia had feminized in recent years, women’s share of migrants was still significantly lower than that of rural dwellers. There was a strong selection into rural-urban migration. In 2007, compared with their rural counterparts who remained in the countryside, rural-urban migrants were significantly younger, more educated, and less likely to have been married. The proportion of current smokers and the household per capita consumption of sugar were both significantly lower among rural- urban migrants than in rural dwellers. Migrants also had marginally significantly (p<0. 1) higher household per capita income than that of rural dwellers. Meanwhile, even though there were no significant differences in self-rated health between the two groups, the share of being overweight was significantly lower among rural-urban migrants than among rural dwellers. These results suggest that rural-urban migrants were positively selected by various sociodemographic and health behavioral factors. However, significantly more migrants were depressed, showing poorer mental health conditions.

Table 1. Descriptive statistics (mean or percentage), Indonesia Family Life Survey (IFLS), 2007 & 2014

	2007			2014		
	All	Rural-urban	Rural	All	Rural-urban	Rural
N	7267	681	6586	7267	681	6586
Health outcome						
Overweight	33.6%	26.9%	34.3%***	47.1%	48.6%	47.0%
Urban life exposure						
Years lived in cities	-	0	-	-	3.6	-
Socioeconomic and demographic factors						
Age	37.0	25.3	38.2***	43.9	32.4	45.1***
Female	55.1%	50.5%	55.6%**	55.1%	50.5%	55.6%**
Education						
Primary school or below	57.2%	23.2%	60.7%***	56.6%	22.3%	60.0%***
Secondary school or above Marital status	42.8%	76.8%	39.3%***	43.4%	77.7%	40.0%***
Never married	21.0%	55.5%	17.4%***	6.2%	21.7%	4.6%***
Ever married	79.0%	45.5%	82.6%***	93.8%	78.3%	95.4%***
HH income per capita ($)	629.3	688.8	622.8+	831.5	1483.6	764.1***
Physical and mental health status						
Self-rated health						
Healthy or somewhat healthy	87.9%	88.8%	87.9%	75.8%	79.9%	75.4%*
Unhealthy or somewhat unhealthy	12.1%	11.2%	12.1%	24.2%	20.1%	24.6%*
Depressed	4.1%	7.3%	3.8%***	21.1%	25.8%	20.6%**
Health-related behaviors						
Walking with moderate efforts in the past week	89.6%	88.4%	90.8%	72.4%	62.6%	73.5%***
Current smoker	33.9%	29.2%	34.4%**	34.4%	34.1%	34.4%
Ever smoker	1.7%	1.2%	1.8%	6.6%	5.3%	6.8%
Never smoker	64.4%	69.6%	63.9%**	59.0%	60.6%	58.8%
HH last sugar purchase in the past month (kg)	0.249	0.213	0.253**	0.287	0.264	0.289
HH last cooking oil purchase in the past month(liter)	0.267	0.241	0.269+	0.363	0.407	0.359*

+ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes: t-test/chi-squared test are conducted to compare rural dwellers/urban residents with rural-urban migrants in each wave.

In terms of the sample descriptive statistics in 2014, there was a considerable increase in the prevalence of overweight for both groups. The increase among rural-urban migrants was especially notable, as the proportion of overweight people in the fifth wave was about 1.8 times that in the previous wave. Besides the rates of overweight, the proportions with depressive symptoms also increased dramatically for both groups. Rural-urban migrants, the group that showed worse mental health in the previous wave, still had a higher proportion of depressed individuals, which was more than 3.5 times higher than the number in 2007.

Compared with rural residents, migrants' advantage in education persisted. Also, although the proportion of never-married among migrants was much lower than that in the previous wave, it was still significantly higher than that among rural dwellers. Moreover, the income gap between migrants and rural dwellers drastically widened with the former's household per capita income being almost two times that of the latter. Interestingly, despite the loss in health advantage of not being overweight over rural dwellers, significantly more rural-urban migrants rated themselves as healthy or somewhat healthy than rural dwellers. In addition, the proportion of rural-urban migrants who were physically active was significantly lower than that of rural dwellers, indicating the adoption of a more sedentary lifestyle over time. For diets, the significant difference between the two groups in the consumption of sugar disappeared, suggesting an increase in sugar consumption among migrants, and they also consumed significantly more cooking oil than rural dwellers.

5.2 Regression Results

The FE regression results comparing rural-urban migrants with rural dwellers are presented in Table 2. The numbers of observations were two times those in the descriptive statistics, as each respondent was compared with themselves in the previous wave and counted as two observations. The first panel shows the results for the pooled sample with both sexes, while the second and third panels display results for women and men, respectively. For each group, nested regression models were constructed. Model 1 included only the key independent variable and socioeconomic factors. Model 2 added controls for physical and mental health conditions. Model 3 further included health- related behaviors. The results for the full model with the interaction term between migration status and gender are shown in the final column.

The first column showed that when only controlling for sociodemographic factors, rural-urban migration was on average associated with a 7.3 percentage point increase in the chance of being overweight ($p<0.01$), holding other variables constant. Marriage was also associated with being overweight. Compared with people who were never married, individuals with marriage histories were on average 4.8 percentage points more likely to be overweight, *ceteris paribus*. Household per capita income was associated with being overweight as well: every one-dollar increase in per capita income was associated with a 1.2 percentage point increase in the probability of being overweight. Education, in contrast, did not predict overweight. After adding physical and mental health to the model, all of the

International Journal of Global Sustainability
ISSN 1937-7924
2024, Vol. 8, No. 1

aforementioned patterns persisted, though they were slightly attenuated. Depression did not predict overweight but self-rated health did. Compared with those who rate their health as unhealthy or somewhat unhealthy, people who considered themselves to be healthy or somewhat healthy were on average 5.1 percentage points more likely to be overweight, *ceteris paribus*. In model 3, when health-related behaviors were included, all coefficients observed in model 2 remained the same, and none of the health-behavioral factors were significant predictors of being overweight.

Table 2. Coefficients from fixed-effects models on overweight status, Indonesia Family Life Survey (IFLS), 2007 & 2014

	Pooled			Female			Male			Pooled
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Full
Residential status										
Rural-urban migrants (ref. = rural dwellers)	0.073**	0.072**	0.073**	0.092**	0.091**	0.090**	0.065*	0.064*	0.066*	0.117***
	(0.023)	(0.023)	(0.023)	(0.034)	(0.033)	(0.033)	(0.030)	(0.031)	(0.031)	(0.032)
Interaction terms (ref. = rural dwellers×female)										
Rural-urban migrants×male										-0.088* (0.042)
Socioeconomic and demographic factors										
Ever married (ref. = never married)	0.048*	0.047*	0.048*	0.037	0.037	0.037	0.045	0.045	0.043	0.046*
	(0.019)	(0.019)	(0.019)	(0.026)	(0.026)	(0.026)	(0.029)	(0.029)	(0.029)	(0.019)
Secondary school or above	0.121	0.117	0.117	0.185	0.172	0.171	0.037	0.041	0.039	0.117
(ref. = primary school or below)	(0.087)	(0.087)	(0.086)	(0.126)	(0.126)	(0.126)	(0.100)	(0.099)	(0.100)	(0.086)
Log HH income per capita ($)	0.012**	0.011**	0.011**	0.012*	0.012*	0.012*	0.009*	0.009*	0.009^{+}	0.011**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Physical and mental health status										
Self-rated health										
Healthy or somewhat healthy		0.051***	0.051***		0.064***	0.064***		0.037^{+}	0.036^{+}	0.051***
(ref. = unhealthy or somewhat unhealthy)		(0.014)	(0.014)		(0.019)	(0.019)		(0.020)	(0.020)	(0.113)
Depressed		-0.000	-0.001		0.006	0.006		-0.007	-0.007	-0.000
		(0.016)	(0.016)		(0.022)	(0.022)		(0.022)	(0.022)	(0.015)
Health-related behaviors										
Walking with moderate efforts in the past week			0.007 (0.014)			0.002 (0.019)			0.015 (0.019)	0.006 (0.014)
Current smoker (ref. = never smoker)			-0.031 (0.030)			-0.045 (0.071)			-0.001 (0.033)	-0.026 (0.030)
Ever smoker			-0.049 (0.035)			-0.025 (0.087)			-0.004 (0.038)	-0.042 (0.035)
HH last sugar purchase in the past month (kg)			0.003 (0.012)			-0.003 (0.017)			0.010 (0.017)	0.003 (0.012)
HH last cooking oil purchase in the past month(liter)			0.011 (0.011)			0.017 (0.016)			0.002 (0.016)	0.010 (0.012)
Observations	14534	14534	14534	8014	8014	8014	6520	6520	6520	

Standard error clustered by household in parentheses $^{+}$ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

The second panel shows results for women. The results are very similar to those for the pooled sample. As shown in Model 3, among women, rural-urban migration was on average associated with a 9.0 percentage point increase in the chance of being overweight, holding other variables constant. The coefficient was larger in magnitude than that of both sexes combined. Marital status no longer predicted overweight but the positive association between household per capita income and overweight remained with a similar coefficient. Education still did not predict overweight. Meanwhile, women who rated their health as healthy and somewhat healthy were 6.4 percentage points more likely to be overweight than those who rated their health as unhealthy or somewhat unhealthy. Still, none of the health behavioral factors significantly predicted overweight.

Results for men are displayed in the third panel. There are similar patterns as observed in previous models: among men, rural-urban migration was on average associated with a 6.6 percentage point increase in the chance of being overweight, holding other variables constant. This coefficient was about 30% smaller than that among women and also lower than that of the pooled sample both sexes combined. Marital status and education were not significantly associated with overweight and the association between overweight and both household per capita income and self-rated health were only marginally significant. Once again, health-related behaviors did not significantly predict being overweight.

For the full model with the interaction term between migration status and gender, it suggested significant differences between men and women for the impact of rural- urban migration on overweight status. On average, migrant men are 8.8% less likely to be overweight than migrant women, holding other variables constant. It demonstrates that women are more vulnerable to the negative influence of rural-urban migration.

The FE regression results comparing rural-urban migrants who spent different lengths of time in urban areas are presented in Table 3, with a similar structure as the previous table. Overall, there were almost identical patterns across the pooled sample and models run separately by gender. Years lived in urban areas did not significantly predict overweight in any of the samples. The impact of marital status remained significant for the pooled sample and marginally significant for migrant women.

Table 3. Coefficients from fixed-effects models on overweight status, rural-urban migrants, Indonesia Family Life Survey (IFLS), 2007 & 2014

	Pooled			Female			Male		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Urban life exposure									
Years lived in cities	0.004	0.004	0.001	0.013	0.014	0.009	-0.008	-0.009	-0.009
	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Socioeconomic and demographic factors									
Ever married (ref. = never married)	0.107*	0.100*	0.093*	0.133*	0.124+	0.119+	0.058	0.052	0.044
	(0.045)	(0.045)	(0.044)	(0.063)	(0.064)	(0.064)	(0.062)	(0.063)	(0.062)
Secondary school or above	0.093	0.102	0.074	0.066	0.021	-0.019	0.122	0.146	0.180

(ref. = primary school or below)	(0.210)	(0.209)	(0.203)	(0.310)	(0.317)	(0.279)	(0.294)	(0.284)	(0.277)
Log HH income per capita ($)	0.008	0.007	0.006	0.008	0.007	0.006	0.006	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.013)	(0.010)	(0.010)	(0.010)
Physical and mental health status									
Self-rated health									
Healthy or somewhat healthy		0.054	0.048		0.091	0.080		0.022	0.011
(ref. = unhealthy or somewhat unhealthy)		(0.039)	(0.039)		(0.055)	(0.054)		(0.051)	(0.052)
Depressed		-0.020	-0.019		0.019	0.017		-0.054	-0.055
		(0.044)	(0.044)		(0.070)	(0.069)		(0.051)	(0.051)
Health-related behaviors									
Walking with moderate efforts in the past week			0.047 (0.041)			0.043 (0.054)			-0.048 (0.062)
Current smoker (ref. = never smoker)			-0.056 (0.059)			0.011 (0.263)			-0.047 (0.056)
Ever smoker			-0.043 (0.120)			-0.359** (0.098)			-0.003 (0.131)
HH last sugar purchase in the past month (kg)			0.054 (0.048)			0.082 (0.068)			0.040 (0.069)
HH last cooking oil purchase in the past month(liter)			0.022 (0.038)			0.040 (0.064)			0.011 (0.050)
Observations	1362	1362	1362	688	688	688	674	674	674

Standard error clustered by household in parentheses $^{+}$ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

6. Discussion

Being overweight has been an emerging health burden that relates to millions of deaths in LMICs. It is closely associated with the rapid urbanization in these countries and will be exacerbated by the continuously increasing number of people who migrate to urban areas from the countryside. However, the impact of rural-urban migration on overweight is understudied in the LMIC context. This study provided new evidence on the association between rural-urban migration and overweight status, and further contributed to the literature by exploring the underlying gender pattern of this association and examining the mediating effects of health-related behaviors, especially diets, which were often missed in the previous literature due to data limitations.

The descriptive results showed that, in Indonesia, rural-urban migrants represented a highly selected group who are younger, better educated, less likely to have marriage histories, and had higher per capita household income than rural dwellers. These patterns of socioeconomic and demographic factors among migrants as compared to rural dwellers are consistent with theories on migration selection (Stark, 1984; Lucas, 1997). Meanwhile, rural-urban migrants were positively selected on health outcomes and health- related behaviors, with a significantly lower prevalence of being overweight and smoking as well as low consumption of sugar than rural dwellers. The positive migration health selection, which was associated with overweight status after migration, would not have been observed in cross-sectional data.

Although rural-urban migrants achieved economic successes, as evidenced by substantially higher household incomes than their rural counterparts, they sacrificed their physical and mental health as well as adopted unhealthy urban lifestyles. They had a much greater increase in the prevalence of overweight over time compared with that of rural dwellers, which was about 1.8 times that before migration. Meanwhile, the proportion of individuals with depressive symptoms among migrants was more than triple that before moving to cities, which was also significantly higher than that among rural dwellers. In addition, rural-urban migrants became less physically active, and more of them became current smokers. They also consumed significantly more sugar and oil.

The results from FE models showed that rural-urban migration was associated with increased chances of being overweight relative to remaining in rural areas. This pattern resonates with previous research in LMICs (e.g. Ebrahim et al., 2010), and is even more striking given the positive selection into migration with respect to both self-rated health and health-related behaviors. Results also demonstrated intriguing departures from those on unhealthy weight in high-income countries. In general, compared with those who considered themselves as unhealthy or somewhat unhealthy, people who rated their health as healthy or somewhat healthy were more likely to be overweight. This finding relates to the traditional thoughts in many LMICs that heavier weight is a symbol of social status and wealth and is pursued by people in these countries (Kim et al., 2010).

In addition, my results revealed an interesting gender pattern in the link between rural-urban migration and overweight status. Overall, women's overweight status was more severely influenced by urban settings than men's, with the magnitude of the coefficient about 30% significantly higher among women than men. This finding adds to the existing literature that documents a higher prevalence of overweight in women by showing women are also much more vulnerable to the negative impact of rural-urban migration on overweight status than men.

My analysis also showed that the chances of being overweight among rural-urban migrants did not vary by the duration of urban residence between the two waves of the survey. This finding is consistent with studies in other LMICs, such as China (Li, 2022) and India (Chilunga et al., 2019). One plausible explanation is that compared with other NCD risk factors (e.g. hypertension) that are asymptomatic until the first attack of disease, overweight has obvious manifestations on the body, such as gained weight or increased waist circumference, and thus is more easily to be noticed and corresponding actions are more likely to be taken to control it. However, it is also likely that the insignificant result is caused by the short time interval between two waves of the survey, eight years, which may not be long enough for the accumulative effect of urban residence on overweight to emerge.

As for the mediating effects of health-related behaviors, although descriptive statistics show that rural-urban migrants did adopt less healthy urban lifestyles after moving to cities, neither these health-related behaviors *per se* significantly predict being overweight nor helped explain the association between urban residence and being overweight. The coefficients of models that control for health behavioral factors are very similar to those that do not. Therefore, the health-related behaviors examined in this study seem to not be the main drivers of the impact of urban residence on overweight, implying that there are other pathways through which urban settings shape weight. Similar findings are documented in a previous study in China (Li, 2022).

This study has some limitations. First, the classification of respondents' residential status was based on the latest two waves of surveys, and it is possible that individuals who were categorized as rural dwellers lived in urban areas before. However, the misclassification would only result in an underestimate of the impact of rural-urban migration on overweight status. Second, the time interval between two waves of surveys is eight years, which might be too short for the cumulative impact of urban residence on being overweight to emerge. However, some variables of interest in this analysis were not included in previous waves, and the residential status for respondents who moved back and forth between rural and urban areas across waves would be hard to define with more waves of data. Therefore, it is impractical for this analysis to use a longer time period. Future research should consider using longitudinal data with a longer follow-up interval to further examine any potential cumulative effect. Third, the health-related behaviors included in this analysis were not complete. The IFLS did not provide information on alcohol use, and its variables on dietary patterns and nutrient intake were also not comprehensive. Overall, longitudinal data that contain both migration history and complete health behavioral factors are rare. This calls for comprehensive data collection on respondents' health-related behaviors so that future studies can conduct more thorough mediation analyses. Finally, although fixed-effects models were used toadjust for migration selection bias and omitted variable bias at individual and wave levels,there were some other biases that cannot be completely ruled out, such as unobserved heterogeneity due to unmeasured characteristics that vary over time. Therefore, casual interpretations of the findings should be made with caution.

In conclusion, this study provided new evidence from longitudinal data that rural- urban migration negatively shapes overweight status in a LMIC context, and that women are more severely impacted than men. More longitudinal studies need to be conducted in other LMICs to see if the chance of being overweight by residential status as well as its gender pattern persist. As the rapid urbanization and extensive rural-urban migration in LMICs continue, governments in these countries should promote a scientific understanding of overweight and spread the knowledge of maintaining healthy weight status in urban communities among rural-urban migrants. Meanwhile, gender-specific intervention programs and policies targeting women should be considered. Women account for a considerable proportion of the migrant population in many LMICs and are more vulnerable to the negative influence of urban settings. In addition, since health- related behaviors examined in this analysis do not mediate between rural-urban migration and overweight, future research should continue to explore other health behavioral factors with more comprehensive data and also discover potential alternative pathways.

Acknowledgments

Not applicable

Authors contributions

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

Funding

Not applicable

Competing interests

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Macrothink Institute.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

References

Achen, C. H. (1982). *Interpreting and using regression* (Vol. 29). Sage.

Allison, P. (2005). *Fixed efects regression methods for longitudinal data using SAS*. Cary, NC: SAS Institute Inc. Andresen, E. M., Malmgren, J. A., Carter, W. B., & Patrick, D. L. (1994).

Screening for depression in well older adults: Evaluation of a short form of the CES-D. *American Journal of Preventive Medicine*, 10(2), 77-84.

Anglewicz, P., VanLandingham, M., Manda-Taylor, L., & Kohler, H. P. (2018). Health selection, migration, and HIV infection in Malawi. *Demography*, 55(3), 979-1007.

Beck, N. (2020). Estimating grouped data models with a binary-dependent variable and fixed effects via a logit versus a linear probability model: The impact of dropped units. *Political Analysis*, 28(1), 139-145. Zhou, B. F. (2002). Predictive values of body mass index and waist circumference for risk factors of certain related diseases in Chinese adults--study on optimal cut-off points of body mass index and waist circumference in Chinese adults. *Biomedical and environmental sciences: BES*, *15*(1), 83-96.

Benatar, S. R. (1998). Global disparities in health and human rights: a critical commentary. *American Journal of Public Health*, 88(2), 295-300.

Brueckner, J. K., & Lall, S. V. (2015). Cities in developing countries: fueled by rural– urban migration, lacking in tenure security, and short of affordable housing. *Handbook of Regional and Urban Economics*, *5*, 1399-1455.

Chilunga, F. P., Musicha, C., Tafatatha, T., Geis, S., Nyirenda, M. J., Crampin, A. C., & Price, A. J. (2019). Investigating associations between rural-to-urban migration and cardiometabolic disease in Malawi: a population-level study. *International Journal ofEpidemiology*, 48(6), 1850-1862.

Cockx, L., Colen, L., & De Weerdt, J. (2017). From corn to popcorn? Urbanization and food consumption in sub-saharan Africa: Evidence from rural-urban migrants in Tanzania. *LICOS Discussion Paper Series*, No. 390/2017

Creber, R. M. M., Smeeth, L., Gilman, R. H., & Miranda, J. J. (2010). Physical activity and cardiovascular risk factors among rural and urban groups and rural-to-urban migrants in Peru: a cross-sectional study. *Revista Panamericana de Salud Pública*, 28, 1-8.

Bonita, R., & Beaglehole, R. (2014). Women and NCDs: overcoming the neglect. *Global Health Action*, 7(1), 23742.

Dinsa, G. D., Goryakin, Y., Fumagalli, E., & Suhrcke, M. (2012). Obesity and socioeconomic status in developing countries: a systematic review. *Obesity Reviews*, 13(11), 1067-1079.

Ebrahim, S., Kinra, S., Bowen, L., Andersen, E., Ben-Shlomo, Y., Lyngdoh, T., Ramakrishnan, L., Ahuja, R.C., Joshi, P., Das, M., Mohan, M., Smith, G. D., Prabhakaran, D., & Reddy, K. S. (2010). The effect of rural-to-urban migration on obesity and diabetes in India: a cross-sectional study. *PLoS Med*, 7(4), e1000268.

Hsu, W. C., Araneta, M. R. G., Kanaya, A. M., Chiang, J. L., & Fujimoto, W. (2015). BMI cut points to identify at-risk Asian Americans for type 2 diabetes screening. *Diabetes Care*, 38(1), 150-158.

Jih, J., Mukherjea, A., Vittinghoff, E., Nguyen, T. T., Tsoh, J. Y., Fukuoka, Y., Bender, M. S., Tseng, W., & Kanaya, A. M. (2014). Using appropriate body mass index cut points for overweight and obesity among Asian Americans. *Preventive Medicine*, 65, 1-6.

Kim, E., Song, J. H., Hwang, J. Y., Ahn, K., Kim, J., Koh, Y. H., Park, M. H., & Jo, S. A. (2010). Obesity and depressive symptoms in elderly Koreans: evidence for the "Jolly Fat" hypothesis from the Ansan Geriatric (AGE) Study. *Archives of Gerontology and Geriatrics*, 51(2), 231-234.

Li, W. (2022). How Urban Life Exposure Shapes Risk Factors of Non-Communicable Diseases (NCDs): An Analysis of Older Rural-to-Urban Migrants in China. *Population Research and Policy Review*, *41*(1), 363-385.

Lu, Y. (2008). Test of the 'healthy migrant hypothesis ': a longitudinal analysis of health selectivity of internal migration in Indonesia. *Social Science & Medicine*, 67(8), 1331-1339.

Lu, Y. (2010). Rural-urban migration and health: Evidence from longitudinal data in Indonesia. *Social Science & Medicine*, *70*(3), 412-419.

Lu, Y., & Qin, L. (2014). Healthy migrant and salmon bias hypotheses: a study of health and internal migration in China. *Social Science & Medicine*, 102, 41-48.

Lucas, R. E. (1997). Internal migration in developing countries. *Handbook of Population and Family Economics*, 1, 721-798.

Mardiansjah, F. H., Rahayu, P., & Rukmana, D. (2021). New Patterns of Urbanization in Indonesia: Emergence of Non-statutory Towns and New Extended Urban Regions. *Environment and Urbanization ASIA*, 12(1), 11-26.

Mayen, A. L., Marques-Vidal, P., Paccaud, F., Bovet, P., & Stringhini, S. (2014). Socioeconomic determinants of dietary patterns in low-and middle-income countries: a systematic review. *The American Journal of Clinical Nutrition*, 100(6), 1520-1531.

Nauman, E., VanLandingham, M., Anglewicz, P., Patthavanit, U., & Punpuing, S. (2015). Rural-to-urban migration and changes in health among young adults in Thailand. *Demography*, 52(1), 233-257.

Neuman, M., Kawachi, I., Gortmaker, S., & Subramanian, S. V. (2013). Urban-rural differences in BMI in low-and middle-income countries: the role of socioeconomic status. *The American Journal of Clinical Nutrition*, 97(2), 428-436.

Peters, R., Amugsi, D. A., Mberu, B., Ensor, T., Hill, A. J., Newell, J. N., & Elsey, H. (2019). Nutrition transition, overweight and obesity among rural-to-urban migrant women in Kenya. *Public Health Nutrition*, 22(17), 3200-3210.

Rachmi, C. N., Li, M., & Baur, L. A. (2017). Overweight and obesity in Indonesia: prevalence and risk factors—a literature review. *Public Health*, 147, 20-29.

Stark, O. (1984). Migration decision making: DeJong, Gordon F. and Robert W. Gardner, eds., (Pergamon, New York, 1981). *Journal of Development Economics*, 14(1), 251–259

Strauss, J., Witoelar, F., & Sikoki, B. (2016). *The fifth wave of the Indonesia family life survey: overview andfield report* (Vol. 1, pp. 1-94). Santa Monica, CA: RAND.

Sukamdi, Mujahid, G. (2015). UNFPA Indonesia Monograph Series: No.3, Internal Migration in Indonesia. *UNFPA Indonesia Monograph Series*. New York, NY, USA: United Nations Population Fund.

Timoneda, J. C. (2021). Estimating group fixed effects in panel data with a binary dependent variable: How the LPM outperforms logistic regression in rare events data. S*ocial Science Research*, 93, 102486.

United Nations. (2018). *The world urbanization prospects: The 2018 revision*. United Nations.

Varadharajan, K. S., Thomas, T., Rajaraman, D., Kurpad, A. V., & Vaz, M. (2013). Overweight and obesity among internal migrants in India. *Asia Pacific Journal of Clinical Nutrition*, 22(3), 416.

Wang, Y., Pan, L., Wan, S. P., Yi, H. W. L., Yang, F., He, H. J., Zheng, L., Zhang, J., Yong, Z. P., & Shan, G. L.(2021). Association between age at arrival, duration of migration, and overweight/obesity in Chinese rural-to-urban migrants: the Yi migrant study. *Chinese Medical Journal*, 134(1), 60.

World Bank. (2020). *Obesity: health and economic consequences of an impending global challenge*. Retrieved May 20, 2021, from https://openknowledge.worldbank.org/bitstream/handle/10986/32383/9781464814 914.pdf

World Health Organization. (2021). *Indonesia: Obesity rates among adults double over past two decades.* Retrieved May 25, 2021, from https://www.who.int/indonesia/news/detail/04-03-2021-indonesia-obesity-rates-among-adults-double-over-past-two-decades

World Health Organization Expert Consultation. (2004). Appropriate body-mass index for Asian populations and its implications for policy and intervention strategies. *Lancet*, 363(9403), 157-163.

World Health Organization. (2020). *Obesity and Overweight Fact Sheet.* Retrieved May 20, 2021, from https://www.who.int/news-room/fact-sheets/detail/obesity-and- overweight

International Journal of Global Sustainability
ISSN 1937-7924
2024, Vol. 8, No. 1

Appendix A. The comparison of binary and continuous model specifications

Table A1. Average marginal effects (AME) of rural-to-urban migration on overweight status

	LPM	Logit
AME	0.053^{**}	0.051^{**}
Standard error	(0.019)	(0.019)
95% Confidence interval	[0.016, 0.090]	[0.013, 0.089]

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Table A2. Average marginal effects (AME) of years lived in cities on overweight status among migrants

	LPM	Logit
AME	0.019^{**}	0.017^{**}
Standard error	(0.006)	(0.005)
95% Confidence interval	[0.008, 0.030]	[0.006, 0.027]

$^{+}$ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

The purpose of the two tables above is to show the comparison between modeling overweight status as binary in logit models and as continuous in linear probability models (LPMs) Therefore, individual and wave fixed effects are not added. As we can see, the two models produce very similar average marginal effects (AME). In other words, treating the binary outcome variable as continuous in this analysis does not impact the accuracy and efficiency of point estimates. The result is consistent with the findings of other empirical works that compare the two modeling strategies. For example, Beck (2020) replicates an article that used the linear probability model by comparing the original results with those generated from the conditional logit model and finds that the magnitudes of the effects and standard errors are almost the same (Beck, 2020).

It is worth noticing that the estimates of models without fixed effects are different from those in the main text from fix-effects models. For example, in table 2, "years lived in cities" significantly predicts overweight status among migrants. However, as shown in the main text, there is no significant association between "years lived in cities" and migrants' overweight status after adding individual and wave fixed effects. This contrast demonstrates the advantage of longitudinal data and fixed-effects models, which adjust for omitted variables that lead to spurious associations.