Is Excess Weight Penalised or Rewarded in Middle-Income Countries' Labour Markets? Comparative Evidence from China, India and Mexico

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Abstract: This comparative study examines the relationship between excess weight and hourly wages in the unprecedented context of middle-income countries. We compare three countries that are at different stages of the nutrition transition: India (at an early stage), China (at an intermediate stage) and Mexico (at an advanced stage). To do so, we use three distinct household surveys and combine different estimation procedures. Our results emphasise a wage reward of underweight together with a wage penalty of excess weight in India, pointing towards the persistence of pro-fat social norms in a country where hunger is still highly prevalent. Conversely, we observe significant overweight and obesity wage penalties in China, especially in non-manual jobs, probably due to a large diffusion of anti-fat social norms in a country where hunger is residual and normal weight predominant. In Mexico, we find an overweight wage premium in manual jobs and no effect in non-manual jobs. We speculate that the large-scale diffusion of excess weight may lead to its greater social acceptance (i.e. 'new' pro-fat norms). Finally, we explore the potential transmission channels through which bodyweight may affect wages. We provide evidence of potential anti-fat discrimination in China and pro-fat-discrimination in India and Mexico. Our results have important implications in terms of public health policy.

Keywords: body mass index, wage, labour market, middle-income countries, China, India, Mexico.

JEL Classification: I15, J31, O10

1. Introduction

In the last decades, the processes of urbanisation, industrialisation and globalisation have led to important lifestyle transformations. These changes mark the occurrence of a worldwide nutrition transition which can be defined as a shift from traditional diets (i.e. rich in cereals and fibres) and physically intensive occupations to more "Westernised" diets (i.e. rich in processed food and fat) and sedentary lifestyles (e.g. inactive occupations and leisure) (Popkin, 1993). Concomitantly, the increasing unbalance between calorie intakes and expenditures has resulted in an epidemiological transition, which can be defined as a decrease in starvation, underweight and infectious diseases together with the emergence of overweight, obesity and related chronic diseases. The generalised weight gain of populations has been particularly intense in rich and middle-income countries. In 2015, 40% of adults worldwide were overweight and 13% were classified as obese. In 2025, estimations suggest that 20% of adults worldwide will be obese (NCD-Risk Factor Collaboration, 2016).

Obesity is a major concern for economists because it induces important costs for society. First, morbidities and diseases related to obesity significantly increase health expenditures (Popkin et al., 2006). Second, obesity is strongly associated with socioeconomic issues. On the one hand, individuals from lower social categories tend to gain weight, and on the other hand, obesity reduces the individual capacity to climb the social ladder by limiting schooling and occupational performances. Given this bidirectional relationship, the literature points out a potential emergence of an obesity poverty trap along with the economic development process (Levasseur, 2019). In this study, we focus on the consequences of obesity on labour market outcomes since employment and wages crystallise both individual economic performances and social well-being (Cawley, 2015). As Cawley (2004) notes, bodyweight may affect labour market outcomes through two channels: *productivity loss* and *social stigmatisation*. While the employer (or the clients) can discriminate an obese worker by choosing not to employ, promote and, or fairly pay him for his level of competence (or not to buy his product/service), the labour environment (ties with peers) forms a social space where an obese worker might be stigmatised and excluded. In addition, stigmatised individuals often suffer from psycho-sociological disorders, such as a lack of self-esteem and self-confidence. Such disorders may lead to self-exclusion from job opportunities, a phenomenon that Cawley (2004) calls "self-discrimination". Furthermore, overweight and obesity are also related to various non-communicable diseases (e.g. diabetes, heart coronary attacks, cancers), as well as chronic fatigue syndrome (e.g. sleeping apnoea, inefficient brain oxygenation). In the labour market, the poor physical and mental health characterising obese workers may cause a *loss of productivity*, through absenteeism at work and presenteeism (i.e. not being productive during the working day).[1]

The existing empirical literature suggests that the impact of bodyweight on professional achievement depends on a country's level of development. Broadly speaking, overweight negatively affects employment and wages in rich economies (e.g. Cawley 2004, Johar and Katayama 2012), while a high body mass index (BMI)[2] still leads to high social positions in poor and traditional societies such as in the Sub-Saharan African region (e.g. Glick and Sahn 1998, Schultz 2003). In these societies, excess weight is generally associated with strength and good health (Renzaho, 2004). However, this issue appears to be more ambiguous in the case of middle-income countries even though empirical evidence remains limited. Some studies identify positive associations between bodyweight and labour market outcomes, similarly to less-developed countries. In India for example, Dinda et al. (2006) find that overweight coal miners have significantly higher wages than their slimmer colleagues. In Brazil, Carrillo et al. (2017) show that bodyweight has a positive effect on wages and access to formal employment. However, most of the studies applied to middle-income countries show more complex evidence. For instance, Colchero and Bishai (2012) suggest that there is no income gap between normal-weight and overweight female workers in Cebu, Philippines. Nevertheless, by restricting the analysis to self-employed or pluri-active women, these authors note that overweight women earn significantly less than their thinnest counterparts. Other studies observe a non-linear causal relationship between BMI and labour market outcomes. In China, Shimokawa (2008) concludes on a U-inverted relationship between BMI and wages with normal-weight workers earning significantly more than thinner and fatter workers. In a study examining the effect of BMI on employment in China, Pan et al. (2013) find the same U-inverted shape. They show that normal-weight adults have a higher probability of working (particularly in good quality jobs) compared to their underweight and overweight peers.

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[1] We do not exclude the possibility that the loss of productivity leads to social stigmatization. Indeed, it is likely that physical and socio-psychological inabilities of obese people keep them from meeting the expectations of employers, peers and/or clients, thus causing social rejection.

[2] BMI is a weight-for-height index commonly used to classify underweight, normal weight, overweight and obesity among adults. BMI is defined as the weight (in kilogrammes) divided by the square of the height (in metres). Its unit is kg/m^2.

Several reasons may explain why the impact of bodyweight on labour market outcomes are unclear within the group of middle-income economies. First, the BMI distribution fundamentally varies across middle-income countries because they are at different stages of their nutrition transition. While lower-middle income countries such as India and Philippines just started their nutrition transition (i.e. persistence of hunger coupled with the emergence of overweight and obesity), upper-middle-income countries such as Brazil, China and Mexico are at a more advanced stage, overweight and obesity becoming a major concern. Second, we can speculate that body-related beauty perception diverges within the group of middle-income countries. Despite the globalisation of thinness ideals, cultural specificities in weight perception and stigmatisation remain (Brewis, SturtzSreetharan and Wutich, 2018). Such cultural heterogeneity potentially makes the relationship between BMI and labour market outcomes ambiguous and hardly generalizable to all middle-income countries.

While numerous studies address the weight-wage relationship in developed countries, the evidence remains scarce in the context of middle-income countries. Further investigation is required to better understand the potential reversal occurring in these countries regarding the relationship between bodyweight and labour market outcomes. Furthermore, the inherent socioeconomic and cultural heterogeneity of the group of middle-income countries point towards the necessity to conduct a comparative analysis, an approach not yet used in the existing literature. To fill the literature gap, we implement a comparative study of the relationship between excess weight and hourly wages for three socio-culturally and nutritionally different middle-income countries. We select China, India and Mexico insofar as these three middle-income countries exhibit extremely different nutritional patterns which potentially makes our findings generalizable to a large spectrum of middle-income economies. While Mexico is a textbook case regarding nutritional and inequality trends for Latin-American countries, both China and India include about two-thirds of the total Asian population. The three countries have undergone significant economic changes in the last decades, leading to shifts in consumption behaviours (Popkin, 2015). In line with the model of nutrition transition, we may argue that Mexico has already reached an advanced stage, China is at an intermediate stage and India just started the process. Indeed, while one-third of Mexican adults are obese, the obesity rates do not exceed 15% in China and 10% in India. In contrast, one-fourth of Indians still suffer from underweight, while this rate does not overpass 5% in Mexico and China (NCD-Risk Factor Collaboration, 2016).

Based on recent waves of Chinese, Indian and Mexican household surveys, we aim to empirically clarify the ambiguous effects of BMI on wages in the context of middle-income countries. We assume that wage penalties related to excess weight increase along with the process of economic development and the nutrition transition. In other words, we expect an excess weight premium in societies like India where obesity is scarce, but hunger persists. Conversely, we expect an excess weight wage penalty in societies where hunger is scarce, but obesity levels are increasingly high, like in China and Mexico. To test these assumptions, we implement gender-specific and country-specific regression analyses using complementary approaches: ordinary least square (OLS), instrumental variables (IV) and propensity score matching (PSM) procedures. In addition to analysing BMI as a continuous indicator, we consider BMI categories and use clinically admitted population-specific cut-offs, instead of the WHO universal BMI cut-offs (i.e. 25kg/m^2 for overweight and 30kg/m^2 for obesity). In each country, we also investigate potential rural/urban heterogeneity, as well as occupational heterogeneity by distinguishing manual occupations from non-manual occupations (i.e. service and high-skilled jobs). Finally, we explore the potential transmission channels through which bodyweight may affect wages. To do so, we examine the impact of bodyweight on the number of hours worked and implement Blinder-Oaxaca decompositions to identify the role of productivity-related factors and potential discrimination in wage gaps.

As expected, our empirical investigations show a shift in the bodyweight-wage relationship along with the process of economic development and the nutrition transition. In India, a lower-middle income country where underweight strongly persists, excess weight is still rewarded among salaried workers. By contrast, we observe significant wage penalties of excess weight in the Chinese labour market, a higher-middle income country where hunger is residual and obesity increases but normal weight still remains predominant. This effect is particularly strong for female and non-manual workers. In Mexico, a higher-middle income country with exacerbated obesity rates, our results suggest an overweight premium in the labour market, particularly for male and manual workers. Finally, although productivity factors contribute to explain the weight-related wage gaps, we also provide clear evidence of potential anti-fat discrimination in China and pro-fat-discrimination in India and Mexico.

The rest of the article is organised as follows. Section 2 establishes the empirical strategy used in the study. Section 3 presents the three datasets and provides summary descriptive statistics.

Section 4 describes and comments the results while Section 5 discusses the main findings in a comparative perspective. Section 6 concludes and provides public policy recommendations.

2. Econometric strategy

To identify the effect of bodyweight on wages, we first estimate Mincer-type wage functions, through OLS, explaining the logarithm of hourly wage by its classical determinants (age, gender, education, etc.) and bodyweight. Because these baseline estimates are exploratory, we test linear and quadratic functional forms of BMI and examine the impact of country-specific BMI clinical categories. Moreover, to investigate the within-country heterogeneity regarding the wage effect of bodyweight, we carry out these baseline estimates for different subgroups based on gender, location (urban-rural) and occupation type.

One important methodological issue facing the identification of a causal relationship between BMI and wages is the potential presence of endogeneity. Indeed, the literature dealing with the labour market consequences of bodyweight has extensively discussed how reverse causality and unobservable heterogeneity may prevent the identification of a causal relationship between BMI and labour market outcomes (e.g. Cawley, 2004, Averett, 2014). In this article, we propose two distinct identification strategies allowing us to observe a potential effect of our variable of interest specified in a continuous (BMI) or categorical (BMI categories) form.

For continuous BMI, we adopt an instrumental variable (IV) strategy and specify linear and quadratic models. As is so often the case in the applied economics literature, identifying a relevant instrument is a great challenge insofar as it must satisfy two conditions: (i) being a good predictor of the endogenous variable (instrument relevance) and (ii) having no effect on the dependent variable (i.e. hourly wage) other than through its influence on the endogenous variable (instrument exogeneity). To ensure that the instrument exogeneity condition is satisfied, the very recent literature tends to increasingly use genetic variables as instruments for BMI or obesity (e.g. Böckerman et al., 2016, Willage, 2018). Such information is unfortunately unavailable for the three middle-income countries analysed in this article. This is the reason why, in line with many studies (e.g. Averett and Korenman, 1996, Cawley, 2004, Shimokawa, 2008, Averett, 2014), we use the average weight of adults' children as an instrument for BMI. The underlying rationale is that the weight of a biological relative can be a proxy of shared genetics that are related to weight and thus can be treated as a valid instrument (Averett, 2014). While this instrument performs very well for India and Mexico, it appears to be a bad predictor of adults' BMI in the Chinese context.[3] We thus choose to use the community average adults' BMI as an alternative instrument for China. This type of instrument has already been used in the literature (e.g. Morris, 2007), even though it is probably more debatable than the first one (Averett, 2014).

To examine the impact of BMI clinical categories on wages, a propensity score matching (PSM) analysis is carried out. Its chief purpose is to estimate the average wage difference between a treatment group (i.e. salaried workers belonging to a specific nutritional group) and a control group (i.e. salaried workers who do not belong to this nutritional category but who present similar characteristics to the treatment group). Since the seminal study of Rosenbaum and Rubin (1983), the PSM approach is widely used to identify causal effects in social sciences. The methodology aims to control for the selection bias on observed characteristics to ensure the comparability between the treatment and the control groups.[4] To do so, it involves a two-step procedure. In the first stage, a probit model explaining the probability of belonging to a specific BMI category by all the relevant observed covariates (i.e. the treatment equation) is estimated. The probabilities predicted from this model are called the propensity scores (i.e. the probability of being treated, conditional to the observed characteristics). In the second stage, salaried workers in the treatment group are matched with salaried workers in the control group who have close propensity score values (and are therefore comparable in terms of observed characteristics). The average treatment effect on the treated (ATT) is then given by the difference between the average hourly wage in the treatment and the matched control groups. We adopt a kernel matching estimator that consists in matching each treated unit to a weighted average of all untreated units, with the greatest weights assigned to units with closer propensity scores (Heckman et al., 1998). Three treatment variables are considered: "being obese", "being overweight or obese" and, exclusively for India, "being underweight". To control for the quality of the matching procedure, we examine the reduction in bias that is the standardised difference in the covariate means before and after matching.

[3] The poor performance for China is probably due to sample restrictions implied by this instrument (i.e. focusing on salaried workers with at least one child). The sample size for China is quite limited compared to the two other countries (2,169 observations) and only one thousand observations remain when restricting the sample to wage earners with at least one child.
[4] One strong assumption of PSM is that there are no unobserved confounders. For a discussion and further details on the PSM approach, see for instance Caliendo and Kopeinig (2008).

Lastly, our empirical strategy aims to investigate the transmission channels through which bodyweight may affect wages. As explained previously, two main channels are identified in the literature: the *productivity channel* and the *discrimination channel*. We first propose to regress the number of hours worked per week on BMI clinical categories and covariates. Such an analysis is informative on how bodyweight status affects access to employment (potential discrimination) and the quantity of work provided (potential compensation of productivity losses). We then propose to disentangle the productivity and discrimination effects on wages by performing Blinder-Oaxaca wage decompositions (Blinder, 1973, Oaxaca, 1973) which consist in decomposing the mean wage gap between group A (e.g. obese) and group B (e.g. not obese). The decomposition uses coefficients from each group's Mincer-type wage equations, yielding the following decomposition equation:

$$\overline{W_A} - \overline{W_B} = \underbrace{(\overline{X_A} - \overline{X_B})\widehat{\beta_A}}_{(1)} + \underbrace{\overline{X_B}\,(\widehat{\beta_A} - \widehat{\beta_B})}_{(2)}$$

$\overline{X_A}$ and $\overline{X_B}$ are productivity-related characteristics held by each group and $\widehat{\beta_A}$ and $\widehat{\beta_B}$ are the returns to those characteristics. This counterfactual method therefore allows distinguishing a component (1) that reflects differences in characteristics (i.e. the "productivity effect") from a component (2) that reflects differences in the returns to characteristics (i.e. the "potential discrimination effect"). This method involves considering a group's wage structure as the reference in the labour market.

3. Data

The empirical investigations are carried out using three distinct household surveys: the China Health and Nutrition Survey (CHNS), the India Human Development Survey (IHDS) and the Mexican Family Life Survey (MxFLS). The CHNS is a longitudinal survey with nine distinct waves from 1989 to 2011 conducted by an international collaborative project involving the Carolina Population Centre (University of North Carolina), the National Institute of Nutrition and Food Safety, and the Chinese Centre for Disease Control and Prevention. The survey is not nationally representative and covers a limited number of provinces. However, these provinces have been selected to provide a diversified picture of geographic and socioeconomic characteristics. Furthermore, CHNS data are representative of rural and urban areas and of each province. In this article, we focus on the 2011 wave. Due to the sample restrictions that are described above, seven provinces or municipalities are included in the empirical analysis, namely: Beijing, Shanghai, Liaoning, Heilongjiang, Jiangsu, Shandong and Henan. The IHDS is a nationally representative household survey with two longitudinal waves (2004-2005 and 2011-2012) conducted by the National Council of Applied Economic Research and the University of Maryland. In this study, we use the 2011-2012 wave. The MxFLS contains a representative sample of the Mexican population at national, rural-urban and regional levels. The MxFLS has been developed and managed by researchers from the Iberoamerican University and the Mexican Centre for Economic Research and Teaching in collaboration with researchers from Duke University. The survey covers a 10-year period with three longitudinal waves (2002, 2005-2006 and 2009-2012). Given the comparative perspective of this article, we only focus on the 2009-2012 wave.

For the three countries, our analysis focuses on salaried workers and wage earners aged from 18 to 65 (excluding pregnant women). Salaried workers being more likely to suffer from wage discrimination than self-employed individuals or employers, we exclude the latter groups from the analysis. Indeed, the sources of discrimination differ between several work statuses. While obese employees are generally stigmatised by their employer and/or colleagues, self-employed workers and employers are mostly prone to facing discrimination from clients.

The dependent variable is the natural logarithm of hourly wages from the main job. For China, it is calculated by combining the annual wage and information on the number of hours worked during the week prior to the survey. For India, the hourly wage is calculated by combining information on the number of working days in the last year, the average hours worked in a day, the frequency and the rate of payment. For Mexico, it is calculated using the wage from the principal activity during a regular month and the number of working hours during a regular week from this principal activity. The top and bottom 1% of the wage distributions are excluded to account for outlier bias. To ensure between-country comparability, hourly wages are expressed in PPP-adjusted US dollars.[5] Our main variable of interest is the body mass index (BMI).

[5] PPP adjustments are carried out using the OECD factor conversions.

Given the different sample restrictions, the number of adults for whom information on the BMI and hourly wages is available is: 2,169 for China; 28,054 for India; and 6,004 for Mexico. In each national survey, weight and height are measured with an objective procedure (using stadiometres and weighting machines). As explained earlier, we also use BMI clinical categories (i.e. obesity, overweight and, for India, underweight). More specifically, we use population-specific BMI thresholds instead of the commonly used WHO universal thresholds. Indeed, several epidemiological studies observe that the prevalence of BMI-related diseases (diabetes, heart attacks, etc.) is not only country-specific but also ethnicity-specific (Wickramasinghe et al., 2005, Misra, 2015). In Mexico for instance, the locally admitted thresholds for overweight and obesity do not differ from international standards. Indeed, the Mexican Official Norm for the Treatment of Overweight and Obesity approves the WHO classification of BMI.[6] Consequently, we consider Mexicans with a BMI higher than 25kg/m² and 30kg/m² as being overweight and obese, respectively. However, for Asian countries, the existing literature strongly recommends using lower thresholds. Indeed, Asians tend to have a higher percentage of body fat compared to Caucasians and Hispanics, especially abdominal visceral fat (Shai et al., 2006), resulting in different associations between BMI and health risks. Overweight and obesity thresholds should even be different across Asian countries given the ethnic heterogeneity (Meeks et al., 2016). For the Chinese population, Zhou and Cooperative Meta-Analysis Group of the Working Group on Obesity in China (2002) set the overweight threshold at 24kg/m² and the obesity threshold at 28kg/m². The China-specific obesity cut-off (28 kg/m²) has the best sensitivity and specificity to identify health conditions, including hypertension and diabetes. Both Chinese thresholds are now extensively used in the empirical literature. For the Indian population, the literature suggests the use of lower thresholds compared to China. Indeed, the seldom-used Consensus Guidelines of Associations of Physicians (Misra et al., 2009) defines overweight and obesity at BMI thresholds that are respectively higher than 23kg/m² and 25kg/m². Even if these thresholds seem surprisingly low, further studies reveal similar cut-offs for countries facing both hunger and obesity such as India (Pradeepa et al., 2015). For this type of countries, the WHO Expert Consultation (2004) finds a "trigger point" relative to a substantial increase of health risks at 23kg/m².[7] Moreover, based

[6] Available on: http://dof.gob.mx/nota_detalle.php?codigo=5154226&fecha=04/08/2010.

[7] In the case of Malaysia, where hunger and obesity are relatively high, Cheong et al. (2013) show that BMI cut-offs of 23kg/m² in men and 24kg/m² in women are appropriate for classification of overweight in terms of cardiovascular risks.

on risk factors and morbidities, the WHO (2000a) recommends using an obesity cut-off of 25 kg/m² for Asian Populations. Therefore, we select the 23kg/m² and 25kg/m² cut-off points for India.

For each regression, we consider classical determinants of wages as control variables. These control variables are age, squared-age, gender, type of occupation (manual workers, service workers and high-skilled workers), education (the highest level of achieved education), the marital status (married or not in China and India; in couple or not in Mexico), the number of children under 15 years old in the household. We add variables controlling for geographical differences: the province (China) or region (India and Mexico) and the residence area (urban or rural). Country-specific variables indicating ethnicity in the case of Mexico (coded 1 if the considered adult is Amerindian) and religion/caste in the case of India (Upper Castes, Scheduled Castes and Tribes, Other Backward Castes, Muslims and other) are also included.

(Insert Figure 1 and Table 1)

Figure 1 presents the distribution of BMI for the three countries, which appear to be at different stages of the nutrition transition, with Mexico at a more advanced stage, China at an intermediary stage and India at a lower stage. Table 1 confirms this intuition, showing that the mean BMI among salaried workers ranges from 21.3kg/m² in India to 24.1kg/m² in China and 27.2kg/m² in Mexico. In India and Mexico, there are no clear gender BMI gaps, but in China, men have an average BMI higher than 1.4kg/m² compared to women. In terms of location and occupation, there are no BMI differences in China. By contrast, in India and Mexico, the mean BMI tends to increase with the quality of occupation (from manual occupations to high-skilled occupations) and urban individuals are fatter than rural ones.

(Insert Table 2)

Figure 1 is also informative on the shape of the BMI distribution, which is less normal in Mexico than in India and China, suggesting a higher prevalence of overweight and obesity. Percentages of nutritional categories, reported in Table 2, confirm this assumption. Note that the BMI cut-offs used in Table 2 are based on the universal guidelines fixed by the WHO (WHO, 2000b): (<18.5kg/m²) for underweight; (18.5-25kg/m²) for normal weight; (25-30kg/m²) for overweight; and (>30kg/m²) for obesity. This table shows a persistence of underweight among Indian workers (23.7%), whereas this nutritional status is residual in China (3%) and Mexico (1.5%). The proportion of salaried workers affected by overweight or obesity is also informative on country differences. While overweight and obesity are little prevalent in India (15.4%), they reach high levels in China (36.2%) and even more in Mexico (65.5%). Moreover, Table 2 emphasises interesting gender differences. In China, the proportion of overweight and obesity is significantly higher for male salaried workers than for females (43.5% against 26.2%). In Mexico, men are clearly more subject to overweight than women (41.2% against 37.1%) but suffer slightly less from obesity (24.8% against 27.4%). By contrast, in the Indian context, gender differences seem less concerning.

Tables 1 and 2 also report descriptive statistics on the mean hourly wage in the three countries. While the hourly wage is higher for men than for women in China and India, the gender wage gap is not significant in Mexico (Table 1).[8] Not surprisingly, the mean wage increases with the quality of occupation in the three countries and is also higher in cities than in rural areas. Crossing the hourly wages and the BMI clinical classification (Table 2) points out interesting differences between countries. In China, higher average wages are observed for underweight and normal weight categories compared to overweight and obesity, for both men and women. In India and Mexico, the opposite is true with an increase in average hourly wages from underweight to obesity.

4. Results

4.1. The bodyweight-wage relationship

Our different estimates of the relationship between bodyweight and wages for the three countries are reported in Tables 3 to 9. For readability purposes, we only report the effects of interest (i.e. the wage effect of BMI and BMI categories). The complete regressions including coefficients of control variables can be found in the Appendix (Tables A1 to A12).

China

[8] This result is due to the high proportion of women among top wages in Mexico. In line with Bhalotra et al. (2015), our t-test shows a non-significant wage gap across gender groups.

OLS estimates for China are reported in Table 3. No significant overall associations are found for men. However, our estimations highlight interesting results in terms of subgroups. We first observe a U-inverted relationship between BMI and wages for rural and manual workers. For manual jobs, for instance, the turning point is reached at a BMI equal to approximately 26kg/m² (between the overweight and obesity cut-offs). This suggests a wage reward of excess weight in such jobs but only to a certain extent. For men, we also observe a decreasing wage effect of overweight in urban areas and a reducing wage effect of obesity among service workers, which could support the idea of excess weight-related wage penalties among white-collar jobs. For service workers, the wage penalty is quite strong since being obese decreases hourly wages by 16%. For the female sample, being obese is strongly and negatively correlated to wages (-14%). When looking at different subgroups, we find a clear wage penalty related to excess weight for service workers (i.e. a negative correlation between BMI and wages and, a wage penalty of obesity). Interestingly, it should be noted that the wage penalty of obesity among female service workers is even higher (-26%) than that observed among male service workers (-16%). Moreover, significant fitted coefficients for urban areas could indicate wage penalties linked to excess weight but these effects are only significant at the 10% level.

(Insert Tables 3 to 5)

To verify whether these baseline correlations represent a potential causal relationship between bodyweight and wages, we complete our findings with two complementary approaches: an IV approach and a PSM approach. IV estimates for China are presented in Table 4. Both linear and quadratic functional forms are tested and the instrument for BMI is the community average adults' BMI. IV estimates emphasise a negative effect of BMI on hourly wages. One additional unit of BMI results in a decrease of approximately 4% of the hourly wage, both for men and women. More specifically, these negative effects particularly concern urban and service workers and are stronger for women than for men. For women, a negative effect is also observed for high-skilled workers. However, the excess weight premium previously observed for manual and rural male workers is unverified in the IV model. The second step of our identification strategy is based on a PSM approach applied to country-specific BMI clinical categories. The ATT are reported in Table 5. To check for the quality of the matching procedure, Figures A1 in the Appendix reports the standardised bias for each covariate before and after matching. Given the relatively low levels of standardised bias after matching, we assume that treated and control groups are similar and comparable, conditional on the set of observed characteristics.

Broadly speaking, PSM results tend to confirm our previous findings. For men and women, we observe the presence of overweight and/or obesity penalties in urban settings and service jobs. Once again, the wage penalties related to excess weight in service jobs are high (around -20%). Moreover, as previously evidenced with IV estimates, PSM suggests significant excess weight penalties for women working in high-skilled jobs (-17.8%).

In a nutshell, three main conclusions can be drawn from our empirical investigations for China. First, our results indicate the existence of wage penalties linked to excess weight among male and female salaried workers, even though these effects are not systematically significant, depending on gender and estimation method. Second, OLS estimates emphasize a U-inverted relationship between BMI and wages for male manual workers indicating a wage reward of excess weight up to a certain level. As already shown by Huang et al. (2016), there is a relative social acceptance of (moderate) excess weight in rural areas and manual jobs. In such jobs, overweight could be a sign of muscular strength. However, this non-linear relationship is not confirmed with IV estimates, suggesting that the U-inverted shape is probably driven by unobservable factors. Third, our estimates globally show that excess weight negatively affects wages in urban areas and service jobs, both for men and women. We also find slight evidence of excess weight penalties among women working in high-skilled jobs. These results suggest that excess weight is strongly penalised in (urban) white-collar jobs, especially among women, which is fully in line with the conclusions of Huang et al. (2016).

India

In the case of India, OLS regressions suggest that BMI is positively and linearly associated with hourly wages for all women (Table 6). A one-unit increase in BMI is associated with a 1% increase in female hourly wages. The OLS analysis based on BMI categories show that overweight and obese women earn significantly more than normal-weight women. However, there is no significant wage gaps between normal weight and underweight women. For men, OLS estimates suggest a U-inverted relationship between BMI and hourly wages, especially in urban areas and white-collar jobs, with a turning point around 25kg/m^2 (which corresponds to the obesity threshold in India). In terms of nutritional categories, Table 6 highlights a wage reward related to overweight among male workers, at least in urban areas. Conversely, underweight men earn significantly less than normal-weight men in each subsample.

(Insert Tables 6 to 8)

Table 7 presents IV estimates in which the average weight of children aged between 0 and 10 years old (adjusted for age and gender) is used as an instrument. We find that, both for men and women, the effect of BMI on wages is significant, positive and generally linear, except for male service workers (non-significant effect) and female rural workers (U-inverted association). Interestingly, IV estimates also point out that the positive effects of BMI on wages are stronger in white-collar jobs than in manual jobs. In Table 8, PSM estimates show that being underweight significantly decreases hourly wages for both men (-7.9%) and women (-4.3%).[9] By contrast, there is a positive wage effect of being above the India-specific overweight and obesity thresholds. Overweight men and obese men earn respectively 8.5% (8.8% in the case of women) and 5.5% (7.3% for women) more than their thinner counterparts. Despite slight locational and occupational differences, PSM estimates globally suggest that underweight tends to be penalised in India, whereas overweight and/or obesity are rewarded.

The following main conclusions can be drawn regarding India. First, the existence of wage penalties of underweight highlights the status of India as a country that still needs to tackle undernutrition due to its harmful consequences on welfare (as shown by the wage penalties) and its potential negative effects on productivity. Second, the effect of BMI on wages is linear and positive in most subgroups, after controlling for endogeneity. We also emphasise wage rewards for overweight and obese individuals. Our results are consistent with the findings from Dinda et al. (2006) who find an obesity premium for Indian coalminers. The wage reward of excess weight may suggest that there is pro-fat discrimination in the Indian society, even in urban areas where western norms of thinness may have more influence. Furthermore, the strong positive effect found among service and high-skilled workers is consistent with empirical studies that observe an overrepresentation of individuals with excess weight in higher socioeconomic groups (Subramanian, Perkins and Khan, 2009, Kulkarni, Kulkarni and Gaiha, 2016), which might indicate possible mechanisms of nepotism.

Mexico

[9] As for China, we check for the quality of the matching procedure in Figures A2 in the Appendix. Once again, the matching procedure significantly reduces observed differences between treated and control groups, and makes both groups statistically comparable conditional on the set of observed characteristics.

Among Mexican male salaried workers, OLS regressions (Table 9) show that the higher the BMI, the higher are the wages. However, the amplitude is weak: a one-unit increase in BMI is associated with a 1% increase in hourly wages. Based on BMI clinical classification, we find that male overweight and obese workers respectively earn 6.9% and 8% more by worked hour than their normal weight counterparts. By looking at subgroups, we observe clear wage rewards related to overweight and obesity for urban and manual workers. The results also show a positive association between BMI and wages among male high-skilled workers, but nutritional categories are not significant for this subgroup. For the whole female sample, we do not observe any significant correlation. However, our results provide evidence of wage rewards related to excess weight for female manual workers. For this subgroup, obesity increases hourly wages by 23.8%.

(Insert Tables 9 to 11)

As for India, the average weight of children aged between 0 and 10 years old (adjusted for age and gender) is used as instrument in the IV procedure. These estimates are presented in Table 10. After controlling for endogeneity, the effect of BMI on wages remains significant and positive for men and becomes positive and significant for women. Moreover, with IV estimates, the effect of BMI on hourly wage is higher than the OLS estimates: one extra BMI unit leads to an increase of hourly wage by 3% for men and 3.9% for women. The positive relationship between BMI and wages for manual workers is also confirmed, both for the male and the female samples. We do not find any significant effects for other occupation groups. PSM estimates (Table 11) are globally in line with IV estimates and suggest an overweight premium, especially for men and manual workers (both male and female).[10] In manual jobs, for instance, PSM estimates highlight wage premiums related to being overweight or obese around +11% for men and +19% for women. Regarding location-specific estimates, the ambiguous results do not allow concluding on a clear relationship between BMI and wages

To sum up, two main trends characterise the BMI-wage relationship in Mexico. First, there is a clear overweight premium in Mexican salaried jobs, especially for men and manual workers. One might consider that larger bodies are preferred in physically intense jobs because a higher BMI is still associated with strength and vitality whereas thinness is a sign of fragility

[10] As for the two other countries, Figure A3 in the Appendix confirms the quality of the matching procedure for Mexico.

(Guendelman et al., 2011, Slade, 2017). Second, the absence of significant weight penalties in non-manual jobs suggests a mutation of bodyweight perceptions in the Mexican society, as assumed in higher-middle income countries (Brewis, SturtzSreetharan and Wutich, 2018). The potential co-occurrence of anti-fat and pro-fat social norms in Mexico can make the relationship highly ambiguous, especially for women and white-collar workers who are particularly concerned by social changes (Mancilla-Díaz et al., 2012, Brewis, SturtzSreetharan and Wutich, 2018). In addition, it may be argued that the introduction of e-technologies (e.g. smartphones, tablets) and new production methods (e.g. teleworking) in the service sector this last decade in Mexico may also contribute to offset the initial productivity losses induced by physical morbidities and obesity-related diseases. It means that technological changes might improve labour market participation and wages of excess weight individuals, given that such changes decrease the proportion of physically demanding jobs (Philipson and Posner, 1999). In other words, technological innovations tend to make obese people more adapted to the labour market.

4.2. From bodyweight to wages: exploring the transmission mechanisms

In this section, we explore potential mechanisms through which bodyweight and wages can be linked. We first analyse how BMI categories explain the number of worked hours. Such an analysis is informative on how the productivity and discrimination channels influence access to employment and quantity of work provided. These results are presented in Tables 12, 13 and 14, respectively for China, India and Mexico (complete regressions are in the Appendix, Tables A13 to A15). Then, we implement Blinder-Oaxaca hourly wage decompositions to measure which proportion of the wage differential between BMI categories is due to differences in productivity-related characteristics of each group (i.e. observed factors) and which proportion is potentially due to (pro-fat or anti-fat) discrimination (i.e. unobserved factors). Decompositions results are reported in Table 15.

China

For China, the regression of the number of hours worked per week on BMI clinical categories and covariates (Table 12) emphasise that male obese workers significantly work longer than their thinner counterparts. In terms of occupational groups, this positive correlation is only significant for service workers with 3 extra-hours worked per week. Given that we previously observed a wage penalty for this category of workers, we assume the presence of an offsetting effect. Put differently, obese male service workers probably *seek access* to more working hours work in order to compensate the loss of productivity and the wage penalties they face. It is interesting to note that we fail to observe a similar effect for obese female service workers while they are also concerned with wage penalties.

(Insert Tables 12 to 15)

The Blinder-Oaxaca decompositions give interesting additional evidence (Table 15). We only observe significant "potential discrimination" of excess weight for the female sample. More precisely, for overweight and obese women, the share of the wage gap that is not explained by productivity-related factors reaches approximately 38%[11] for overweight and obese women and 39% for obese women. In terms of subgroups, there is clear evidence of a strong potential discrimination of excess weight among female service workers. The anti-fat discrimination against overweight and obese workers represents approximately two-thirds of the wage gap. Lastly, there is slight evidence of anti-fat discrimination for overweight and obese women working in high-skilled jobs. The existence of excess-weight-related discrimination against Chinese female workers has already been emphasised in the literature and, undoubtedly, the "aesthetic channel" is crucial to explain the development of such discrimination (Pan et al. 2013, Tafreschi, 2015, Huang et al., 2016). As explained by Tafreschi (2015: 131), "females often face stronger societal pressures to conform to thin body shapes (determined by cultural norms and media images)".[12] Moreover, the literature has shown that these ideals of thinness are more pronounced among white-collar occupations and higher socioeconomic status groups (Luo, Parish and Laumann, 2005, Xiao et al., 2013, Bonnefond and Clément, 2014, Huang et al., 2016, Clément, 2017). For instance, as argued by Huang et al. (2016), the westernization of beauty ideals exacerbates wage penalties in white-collar occupations because these jobs imply important interpersonal relations with colleagues and customers compared to manual jobs.

India

[11] 0.099 divided by 0.259.

[12] The diffusion of the Western body image of thinness for women can be exemplified by the "#A4waist challenge" consisting in holding a piece of A4 paper vertically in front of their stomach to demonstrate their slender waist. See for instance: https://www.washingtonpost.com/news/the-intersect/wp/2016/04/07/the-counterintuitive-reason-why-chinese-body-shaming-memes-conquered-the-web/?utm_term=.ecec73810519

In India, we find gender-specific patterns of the relationship between weight and worked hours (Table 13). For men, all BMI categories are significantly correlated with the number of worked hours. Being underweight reduces by 1.1 hour the number of worked hours per week whereas being in overweight and obesity categories increase the number of worked hours by 1.4 and 2 hours, respectively. The results are similar in the manual workers subsample. However, for non-manual workers, only obesity status increases working time, with a large coefficient for high-skilled workers (3 extra-hours). For women, only the Indian obesity category is significantly positively related to the number of worked hours. These results suggest that individuals with a higher BMI are more likely to *gain access* to working hours through positive discrimination and/or they are more likely to *seek access* to more working hours to compensate for the loss of productivity.

The decomposition results (Table 15) show that, in the Indian case, the wage gap between underweight and normal-weight individuals is mostly due to differentials in productive characteristics. However, about 23% of the wage gap for men and 19% for women is due to potential discrimination against extreme thinness. The trends are generally the same for each employment category. In addition to having a higher productive ability, overweight workers also partly beneficiate from a potential discrimination effect, but this time in favour of excess weight. This pro-fat discrimination accounts for about 37% of the overweight premium in the male and female sample, illustrating that a higher BMI is considered as a sign of productivity, thus rewarding weight, regardless of human capital factors. This pro-fat discrimination may also be interpreted in terms of nepotism in favour of fatter individuals.

Mexico

In Mexico, we do not find any significant correlation between BMI categories and the number of hours worked per week for the female sample (Table 14). For the male sample, however, there is a positive association between obesity and the working time (1.3 extra-hours), which is even stronger for male service workers (2.4 extra-hours). As previously discussed for India, the higher quantity of worked hours for service workers in excess weight can be explained by a *gain access* effect and/or a *seek access* effect.

In Table 15, the Blinder-Oaxaca hourly wage decompositions provide additional information about the productivity and discrimination channels. We find that there is a potential positive discrimination of overweight in Mexico, especially for men for whom 53% of the overweight premium is unexplained by productivity-related factors. Occupation-specific estimates suggest that this potential pro-fat discrimination is stronger for manual workers. Indeed, respectively for men and women, 82% and 134% of the overweight/obesity premiums remain unexplained. Interestingly, in service and high-skill jobs, productivity-related differences account for the larger part of wage gaps between overweight/obese and normal-weight workers. Given the absence of weight-related wage discrimination for Mexican white-collars, we can speculate that the higher quantity of work provided by overweight and obese service workers (Table 14) is mainly due to their lower productivity level. In other words, even if they do not suffer from wage penalties, they need to work more hours to generate the same level of production (i.e. *seek access* to working hours). Of course, the higher quantity of worked hours for service workers suffering from excess weight is likely to be facilitated by technological innovations and the introduction of new working methods (e.g. teleworking).

5. Discussion

The existing literature is ambiguous about the appreciation of weight in the labour market of middle-income countries. A doubt remains on whether excess weight leads to wage penalties or by contrast to wage rewards. To better understand this issue, this study compares the BMI-wage relationship in three middle-income countries. Focusing on China, India and Mexico enables us to provide comparative insights on the evolution of the BMI-wage gradient insofar as these countries are at different stages of the nutrition transition. We use an IV strategy and a PSM approach to identify the causal effects of overweight and obesity (and underweight in the Indian context) on hourly wages. Moreover, we examine the productivity and discrimination channels through which bodyweight may affect wages (i.e. using Blinder-Oaxaca hourly wage decompositions).

Broadly speaking, our results emphasise specific weight-related relationships depending on the nutrition transition stage. In lower-middle income countries that just started their nutrition transition such as India, the emergence of overweight is often associated with the persistence of hunger. The labour market of these societies strongly reflects the (not so far) past nutritional deprivations (Renzaho, 2004). Indeed, our results show that, while underweight salaried workers suffer from significant wage penalties, overweight and obese salaried workers benefit from higher wages. These findings are an important contribution for the scarce literature that focused on lower-middle income countries such as India. In the coming decades, one can speculate that the form of the relationship will change in such countries, when a more advanced stage of nutrition transition will be achieved. In higher-middle income countries characterised by an intermediate stage of nutrition transition such as China, hunger is residual but overweight is becoming an alarming concern. Nonetheless, despite the fast increase in overweight, normal weight remains the standard bodyweight status in the Chinese society. Hence, in line with the existing literature (e.g. Shimokawa, 2008, Huang et al., 2016), we find significant overweight and obesity wage penalties in the Chinese labour market, especially in white-collars jobs. By contrast, manual and rural workers are not concerned by such penalties induced by excess weight. The absence of overweight penalties might suggest a notable persistence of traditional beliefs in rural and manual occupations. Finally, in higher-middle income countries at an advanced stage of nutrition transition, such as Mexico, overweight is predominant and constitutes the standard bodyweight status in society. This nutritional specificity seems to have a direct influence on the BMI-wage relationship. Our results show significant overweight and obesity premiums in the Mexican labour market, especially for male and manual workers. Moreover, we fail to emphasise any significant wage penalty in other occupation groups. This is consistent with studies that find an increasing social acceptance of excess weight emerging from the recent spread of overweight in society, not only in the US context (Robinson and Christiansen, 2014, Classen, 2017), but also in the Mexican context (Prina and Royer, 2014). Likewise, Gwozdz et al. (2019) point out that bodyweight status and nutrition-related behaviours strongly depend on the environment where one lives and develops (i.e. through peer effects). Overweight individuals tend to influence peers' behavioural patterns, especially in terms of unhealthy food consumption and physical inactivity. Regarding labour market outcomes, Kropfhäußer and Sunder (2015) and Barbieri (2018) find an overweight premium in the UK and Germany, two rich regions where excess weight has rapidly increased, while one decade earlier overweight was penalised in the UK (Morris, 2007) and not correlated to wages in Germany (Cawley, Grabka and Lillard, 2005).

However, even in countries where obesity is endemic such as Mexico, we find within-country heterogeneity in the BMI-wage relationship. The absence of a relationship between BMI and hourly wages in non-manual jobs in Mexico contrasts with the surprising reward of excess weight in physically demanding activities. The heterogeneous effects based on the type of occupations (i.e. manual vs. non-manual), as observed in China and Mexico, have already been discussed in previous studies focusing on rich countries (DeBeaumont, 2009, Caliendo and Gehrsitz, 2016) and middle-income countries (Huang et al., 2016). Overweight penalties are higher in non-manual activities because such jobs may involve strong interpersonal relationships and are potentially more exposed to Western norms of thinness (i.e. diffusion of anti-fat norms). Conversely, as already documented in the literature (Caliendo and Gehrsitz, 2016, Huang et al., 2016, Slade, 2017), our findings for Mexico, and to a lower extent for China, suggest a preference for excess weight workers in manual jobs. This result can be explained by: (i) higher productive abilities of excess weight workers to do manual tasks, and/or (ii) a greater social acceptance of overweight and obesity in physically demanding activities (i.e. a higher perceived productivity).

The ambiguous effects of bodyweight on wages *within* and *between* middle-income countries can partly be explained by anthropological studies. In these countries, Brewis, SturtzSreetharan and Wutich (2018) assume a simultaneous occurrence of weight-positive and weight-negative social norms. Indeed, as these authors (2018: 3) mention, "ethnographic cases [...] indicate that adoption of new anti-fat norms (from the Western culture) need not eradicate pro-fat ones (generally due to past -or current- nutritional privations and socio-cultural beliefs)". It means that the balance between pro-fat and anti-fat social norms is likely to depend on the economic development level and nutritional conditions. The specific situation of India is probably carried by the persistence of pro-fat norms due to the strong prevalence of hunger. In contrast, overweight and obesity penalties for Chinese non-manual workers might be explained by the large diffusion of thinness ideals, coupled with the fact that a large part of the Chinese population still remains relatively thin. The lack of significant effects for manual and rural workers in China might be due to the persistence of pro-fat norms in physically demanding jobs. In Mexico, the intuition is fundamentally the same as in China, apart from the fact that the bodyweight standard is likely to be at a higher BMI level. Hence, we speculate that excess weight is probably more accepted in Mexico than in China given the overrepresentation of overweight and obesity in Mexico. It is probably why we observe significant overweight and obesity premiums in manual jobs, but no significant effects in non-manual jobs.

Finally, these nutrition-related social norms are obviously connected to the transmission channels through which bodyweight may affect wages, i.e. the productivity channel and the discrimination channel. Productivity-related factors such as the worker's abilities and skills contribute to explain the observed wage gaps across bodyweight categories, likewise the introduction of new technologies and production methods (Philipson and Posner, 1999). Nevertheless, Blinder-Oaxaca wage decompositions highlight the occurrence of significant weight discrimination in middle-income countries, thus confirming the crucial role of social norms. In China, we observe a strong potential negative discrimination of excess weight (i.e. anti-fat wage discrimination), particularly among female service workers. By contrast, in India and Mexico, we find potential positive discrimination on the lines of overweight and obesity (i.e. pro-fat wage discrimination).

6. Conclusion

This study provides interesting comparative evidence on the consequences of overweight and obesity on labour market outcomes for middle-income countries. The rise of overweight and obesity is a public health concern with unclear economic implications for the three middle-income countries we analysed. Notwithstanding, our evidence confirms that its labour-market-related mechanisms present between- and within-country heterogeneity.

From our point of view, our findings may inform policy design and implementation. First, regarding labour market policies, our results have implications for the design of anti-discrimination policies. Identifying the subgroups of salaried workers facing strong weight-related discrimination (such as female service workers in China) is of crucial interest to better target anti-discrimination interventions. Second, our conclusions call for the implementation of increased targeting of anti-obesity policies. More precisely, we suggest that obesity prevention interventions such as awareness campaigns or the diffusion of nutrition recommendations would be more effective if targeted in occupation groups among which pro-fat social norms are predominant (i.e. manual workers). Indeed, the existence of pro-fat norms is an alarming concern for developing countries since it may significantly accelerate the global weight gain of populations. However, anti-obesity programmes require a certain sophistication. If not effectively targeted, such interventions may generate negative spill-overs. As explained by Brewis, SturtzSreetharan and Wutich (2018), obesity campaigns may reinforce fat stigma in subpopulations where anti-fat norms are already predominant. This may in return generate psychological stress and deteriorated health outcomes (Puhl and Suh, 2015).

To better design anti-obesity interventions, investigating the potential harmful consequences of anti-fat norms and weight stigma on psychological and physical health is a relevant area for future research. More generally, this study also calls for further investigation regarding weight-related social norms and body perception. We suggest that more extensive anthropological and psycho-sociological research is needed to examine the diffusion of pro-fat and anti-fat social norms in developing societies in order to understand socio-cultural specificities in the degree of acceptance/rejection of excess weight.

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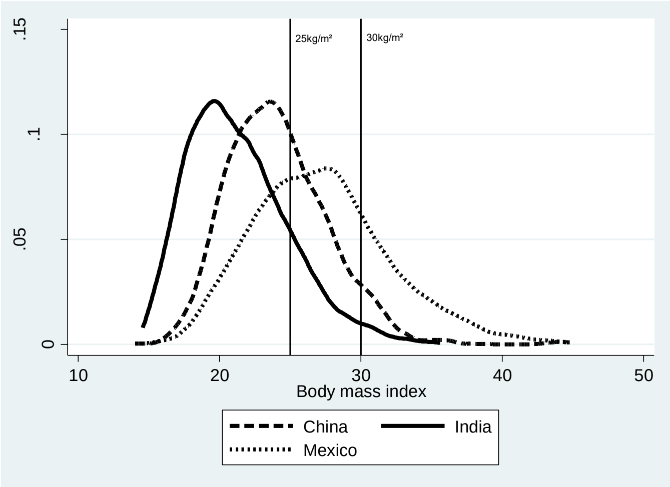
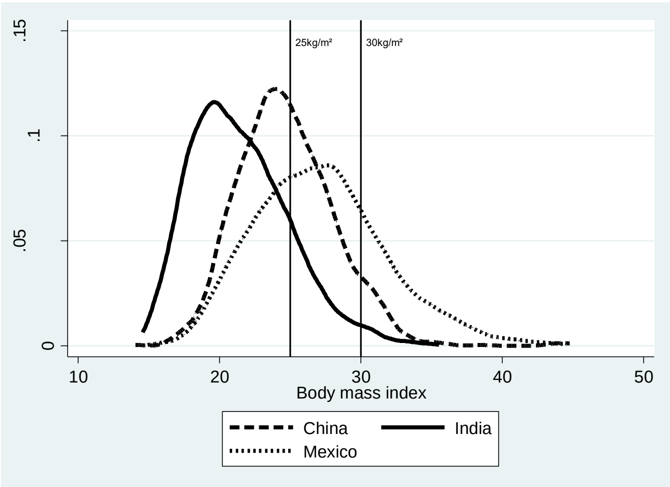
Figure 1: Compared distributions of BMI (Epanechnikov kernel).

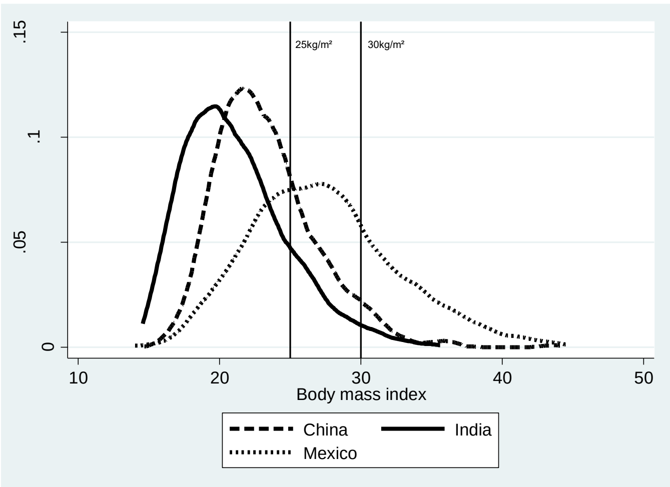
ALL ADULTS



MEN



WOMEN



Sources: CHNS, IHDS and MxFLS. Authors’ calculations.

Table 1: Mean BMI and hourly wage by gender, location and occupation.

	Mean BMI (in kg/m²)			Mean hourly wage (PPP US$)		
	CHINA	**INDIA**	**MEXICO**	**CHINA**	**INDIA**	**MEXICO**
Gender						
Men	24.720	21.419	27.160	4.399	1.857	3.103
Women	23.362	21.168	27.352	3.883	1.157	3.333
Residence						
Urban	24.060	22.819	27.446	4.812	2.324	3.559
Rural	24.296	20.774	26.911	3.157	1.327	2.509
Occupation						
Manual worker	24.245	20.901	26.719	3.036	1.314	2.520
Service worker	24.106	22.720	26.929	3.722	2.106	2.845
High-skilled worker	24.077	23.539	27.838	5.645	3.699	6.219
Total	24.150	21.309	27.227	4.182	1.645	3.175

Sources: CHNS, IHDS and MxFLS. Authors' calculations.

Table 2: Mean hourly wage by BMI categories (WHO cut-offs).

	Proportion			Mean hourly wage (PPP US$)		
	Whole sample	**Men**	**Women**	**Whole sample**	**Men**	**Women**
CHINA						
Underweight	0.030	0.018	0.047	5.020	5.317	4.876
Normal weight	0.608	0.547	0.691	4.299	4.489	4.095
Overweight	0.298	0.363	0.208	3.950	4.265	3.174
Obesity	0.064	0.072	0.054	3.776	4.194	2.982
Total	1.000	1.000	1.000	4.182	4.399	3.883
INDIA						
Underweight	0.237	0.218	0.262	1.090	1.295	0.875
Normal weight	0.609	0.629	0.583	1.491	1.766	1.105
Overweight	0.132	0.134	0.129	2.110	2.552	1.497
Obesity	0.022	0.020	0.026	1.847	1.921	1.390
Total	1.000	1.000	1.000	1.645	1.857	1.157
MEXICO						
Underweight	0.015	0.012	0.021	2.468	2.245	2.817
Normal weight	0.330	0.328	0.334	2.890	2.820	3.028
Overweight	0.398	0.412	0.371	3.219	3.171	3.333
Obesity	0.257	0.248	0.274	3.343	3.397	3.251
Total	1.000	1.000	1.000	3.175	3.103	3.333

Sources: CHNS, IHDS and MxFLS. Authors' calculations.

Table 3: Results of OLS regressions (log hourly wage in PPP US$), CHINA.

	ALL			URBAN			RURAL			MANUAL WORKERS			SERVICE WORKERS			HIGH-SKILLED WORKERS		
MEN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
BMI	-0.005	0.036		-0.009	-0.022		0.005	0.144**		0.002	0.210***		-0.013	-0.035		-0.002	0.021	
	(-0.92)	(0.91)		(-1.55)	(-0.60)		(0.52)	(2.07)		(0.17)	(3.31)		(-1.28)	(-0.29)		(-0.20)	(0.50)	
BMI squared		-0.001			0.000			-0.003**			-0.004***			0.000			-0.000	
		(-1.09)			(0.40)			(-2.13)			(-3.52)			(0.19)			(-0.60)	
Overweight (24-28 kg/m²)[1]			-0.020			-0.087**			0.060			0.033			-0.039			-0.028
			(-0.55)			(-2.03)			(0.97)			(0.52)			(-0.55)			(-0.46)
Obesity (>28kg/m²)[1]			-0.072			-0.076			0.013			-0.026			-0.160*			-0.019
			(-1.45)			(-1.37)			(0.17)			(-0.31)			(-1.89)			(-0.20)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,273	1,273	1,273	764	764	764	509	509	509	410	410	410	406	406	406	390	390	390
R-squared	0.273	0.273	0.273	0.316	0.316	0.318	0.200	0.206	0.201	0.189	0.209	0.190	0.225	0.225	0.226	0.304	0.304	0.304
WOMEN	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
BMI	-0.008	-0.039		-0.005	-0.065*		-0.012	0.021		-0.000	-0.080		-0.017**	0.021		-0.009	-0.037	
	(-1.47)	(-1.14)		(-0.90)	(-1.89)		(-1.27)	(0.18)		(-0.02)	(-0.63)		(-1.99)	(0.26)		(-1.09)	(-0.97)	
BMI squared		0.001			0.001*			-0.001			0.002			-0.001			0.001	
		(0.96)			(1.88)			(-0.27)			(0.62)			(-0.48)			(0.81)	
Overweight (24-28 kg/m²)[1]			-0.060			-0.100*			-0.006			0.033			-0.126			-0.080
			(-1.34)			(-1.89)			(-0.08)			(0.40)			(-1.58)			(-1.12)
Obesity (>28kg/m²)[1]			-0.140**			-0.081			-0.192*			-0.183			-0.262***			-0.131
			(-2.33)			(-1.09)			(-1.95)			(-1.33)			(-2.96)			(-1.03)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	921	921	921	595	595	595	326	326	326	177	177	177	392	392	392	315	315	315
R-squared	0.470	0.470	0.472	0.404	0.406	0.407	0.360	0.360	0.364	0.296	0.298	0.308	0.404	0.404	0.411	0.421	0.421	0.422

Notes: (1) Ref.=underweight and normal weight. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill) and provincial dummies.

Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: CHNS. Authors' calculations.

Table 4: Results from IV regressions, CHINA.

	ALL		URBAN		RURAL		MANUAL WORKERS		SERVICE WORKERS		HIGH-SKILLED WORKERS	
MEN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BMI	-0.038**	-0.252	-0.052***	-0.362	0.013	-0.503	-0.020	-1.287	-0.073***	0.219	-0.039	0.007
	(-2.23)	(-0.81)	(-2.72)	(-1.61)	(0.45)	(-0.46)	(-0.68)	(-1.33)	(-2.88)	(0.32)	(-1.28)	(0.02)
BMI squared		0.004		0.006		0.010		0.025		-0.006		-0.001
		(0.69)		(1.40)		(0.48)		(1.32)		(-0.43)		(-0.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,273	1,273	764	764	509	509	410	410	406	406	390	390
F-stat on excluded	112.22	68.98	48.34	33.94	73.85	37.12	49.36	25.80	55.36	28.15	22.50	18.49
instruments		63.10		32.48		34.37		24.00		27.31		17.31
WOMEN	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
BMI	-0.043**	0.455	-0.046**	0.059	-0.046	3.370	0.008	0.076	-0.115**	15.423	-0.052*	0.297
	(-2.04)	(1.04)	(-2.02)	(0.19)	(-1.04)	(0.86)	(0.12)	(0.02)	(-1.96)	(0.21)	(-1.83)	(0.69)
BMI squared		-0.010		-0.002		-0.068		-0.001		-0.335		-0.006
		(-1.11)		(-0.33)		(-0.87)		(-0.02)		(-0.21)		(-0.80)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	921	921	595	595	326	326	177	177	392	392	315	315
F-stat on excluded	49.59	35.79	32.15	24.36	20.71	11.21	7.18	4.09	15.57	13.70	19.24	11.79
instruments		32.80		21.99		11.04		4.19		13.37		10.46

Notes: (1) We use the community average BMI of the adult population as an instrument. In quadratic specifications, the square of the community average BMI is also included as an instrument. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill) and provincial dummies.
Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.
Source: CHNS. Authors' calculations.

Table 5: Results from PSM analysis, CHINA

		Overweight/obese versus Others				Obese versus Others			
		Overweight and obese	Others	Difference	T-stat	Obese	Others	Difference	T-stat
MEN									
All	Unmatched	1.241	1.256	-0.014	0.38	1.169	1.263	-0.093*	-1.82
	ATT	1.241	1.288	-0.047	-1.18	1.169	1.233	-0.063	-1.19
Urban	Unmatched	1.358	1.450	-0.092**	-2.03	1.329	1.409	-0.080	-1.24
	ATT	1.358	1.446	-0.087*	-1.82	1.337	1.394	-0.057	-0.89
Rural	Unmatched	1.058	0.980	0.078	1.27	0.989	1.031	-0.041	-0.53
	ATT	1.058	1.011	0.047	0.72	1.003	1.014	-0.011	-0.13
Manual workers	Unmatched	1.037	1.028	0.009	0.16	0.974	1.043	-0.069	-0.84
	ATT	1.037	1.037	0.063	0.01	0.974	1.029	-0.055	-0.65
Service workers	Unmatched	1.144	1.258	-0.113*	-1.68	1.058	1.218	-0.159*	-1.76
	ATT	1.144	1.230	-0.086	-1.20	1.058	1.253	-0.195**	-2.22
High-skilled workers	Unmatched	1.525	1.539	-0.014	-0.21	1.463	1.544	-0.080	-0.88
	ATT	1.525	1.555	-0.029	-0.41	1.487	1.411	0.075	0.63
WOMEN									
All	Unmatched	0.912	1.172	-0.259***	-5.15	0.809	1.107	-0.298***	-3.72
	ATT	0.912	1.007	-0.094	-1.54	0.809	0.957	-0.150*	-1.72
Urban	Unmatched	1.159	1.384	-0.224***	-3.88	1.122	1.326	-0.204**	-2.19
	ATT	1.162	1.315	-0.152**	-2.24	1.157	1.221	-0.063	-0.61
Rural	Unmatched	0.533	0.742	-0.209***	-2.74	0.332	0.723	-0.391***	-3.36
	ATT	0.537	0.641	-0.103	-1.06	0.337	0.577	-0.239**	-2.10
Manual workers	Unmatched	0.621	0.651	-0.029	-0.34	0.400	0.676	-0.275**	-2.20
	ATT	0.628	0.721	-0.092	-0.91	0.427	0.620	-0.192	-1.15
Service workers	Unmatched	0.746	1.039	-0.292***	-3.99	0.648	0.959	-0.311***	-2.65
	ATT	0.752	0.956	-0.204**	-2.22	0.648	0.795	-0.146	-1.24
High-skilled workers	Unmatched	1.371	1.545	-0.173**	-2.11	1.334	1.571	-0.237*	-1.86
	ATT	1.387	1.566	-0.178*	-1.89	1.334	1.466	-0.132	-0.78

Notes: (1) ATT are mean-comparison tests where observations are weighted by propensity scores estimated by a Kernel algorithm. Propensity scores refer to the fitted probability of being treated (overweight or obese) versus non-treated conditional on the set of control variables. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill) and provincial dummies.
Level of statistical significance: 1 %***, 5 %**, and 10 %*.
Source: CHNS. Authors' calculations.

Table 6: Results of OLS regressions (log hourly wage in PPP US$), INDIA.

	ALL			URBAN			RURAL			MANUAL WORKERS			SERVICE WORKERS			HIGH-SKILLED WORKERS		
MEN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
BMI	0.016***	0.050***		0.020***	0.093***		0.012***	0.035**		0.013***	0.029**		0.021***	0.128***		0.019***	0.186***	
	(11.45)	(4.07)		(7.79)	(4.11)		(7.42)	(2.30)		(9.37)	(2.22)		(4.36)	(2.79)		(2.99)	(3.26)	
BMI squared		-0.001***			-0.002***			-0.001			-0.000			-0.002**			-0.003***	
		(-2.70)			(-3.20)			(-1.47)			(-1.17)			(-2.35)			(-2.96)	
Underweight (<18.5kg/m²)[1]			-0.051***			-0.091***			-0.032***			-0.033***			-0.132**			-0.161**
			(-5.14)			(-3.56)			(-3.11)			(-3.53)			(-2.44)			(-2.00)
Overweight (23-25 kg/m²)[1]			0.064***			0.086***			0.033**			0.068***			0.015			0.072
			(4.86)			(3.68)			(2.14)			(5.10)			(0.35)			(1.24)
Obesity (>25kg/m²)[1]			0.063***			0.038**			0.059***			0.059***			0.014			0.051
			(8.80)			(2.55)			(7.57)			(8.36)			(0.53)			(1.28)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,905	15,905	34,237	4,809	4,809	12,034	11,096	11,096	22,203	12,588	12,588	25,920	1,797	1,797	4,651	1,134	1,134	2,740
R-squared	0.355	0.355	0.330	0.299	0.301	0.308	0.286	0.286	0.272	0.280	0.280	0.253	0.255	0.258	0.263	0.193	0.199	0.195
WOMEN																		
BMI	0.010***	-0.003		0.018***	0.024		0.006***	0.008		0.005***	0.001		0.019***	0.047		0.024***	0.123**	
	(7.07)	(-0.28)		(5.03)	(0.74)		(4.51)	(0.69)		(3.81)	(0.05)		(3.99)	(1.11)		(3.46)	(2.01)	
BMI squared		0.000			-0.000			-0.000			0.000			-0.001			-0.002	
		(1.08)			(-0.18)			(-0.16)			(0.37)			(-0.66)			(-1.62)	
Underweight (<18.5 kg/m²)[1]			-0.016			-0.051			-0.014			-0.013			-0.050			-0.098
			(-1.54)			(-1.33)			(-1.43)			(-1.38)			(-0.97)			(-1.12)
Overweight (23-25 kg/m²)[1]			0.046***			0.076*			0.037**			0.040***			0.047			0.146*
			(2.91)			(1.95)			(2.33)			(2.80)			(0.92)			(1.77)
Obesity (>25kg/m²)[1]			0.051***			0.099***			0.021*			0.007			0.134***			0.213***
			(4.68)			(3.59)			(1.92)			(0.70)			(3.58)			(3.78)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,119	12,119	14,901	2,628	2,628	3,489	9,491	9,491	11,412	9,709	9,709	11,666	1,499	1,499	1,969	861	861	1,201
R-squared	0.286	0.287	0.307	0.337	0.337	0.344	0.181	0.181	0.185	0.120	0.120	0.116	0.270	0.270	0.292	0.309	0.311	0.297

Notes: (1) Ref.=normal weight. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (married or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and caste/religion.

Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: IHDS. Authors' calculations.

Table 7: Results from IV regressions, INDIA.

	ALL		URBAN		RURAL		MANUAL WORKERS		SERVICE WORKERS		HIGH-SKILLED WORKERS	
MEN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BMI	0.087***	-13.483	0.144***	9.448	0.056***	1.425	0.065***	16.699	0.147	1.891	0.144**	9.562
	(0.020)	(100.193)	(0.046)	(17.982)	(0.020)	(2.254)	(0.020)	(497.029)	(0.090)	(1.403)	(0.059)	(14.729)
BMI squared		0.318		-0.212		-0.032		-0.394		-0.042		-0.201
		(2.349)		(0.407)		(0.053)		(11.775)		(0.032)		(0.0315)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,968	6,968	1,834	1,834	5,134	5,153	5,716	5,716	678	678	419	419
F-stat on excluded	78.07	48.93	19.53	14.48	63.25	36.00	63.86	41.95	6.81	6.08	12.66	6.39
instruments		44.20		13.21		32.76		38.03		5.57		5.94
WOMEN	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
BMI	0.050***	12.365	0.160***	1.975*	0.015	-0.732	0.006	0.411	0.180**	-3.386	0.179**	1.853
	(0.019)	(50.486)	(0.059)	(1.044)	(0.018)	(1.253)	(0.018)	(2.054)	(0.083)	(8.052)	(0.087)	(2.394)
BMI squared		-0.288		-0.041*		0.018		-0.010		0.075		-0.037
		(1.179)		(0.022)		(0.030)		(0.049)		(0.173)		(0.054)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,321	5,321	974	974	4,347	4,347	4,365	4,365	571	571	371	371
F-stat on excluded	72.27	50.43	14.22	14.40	56.70	36.81	56.16	40.94	6.60	6.68	8.51	4.84
instruments		48.15		14.89		34.41		38.41		7.06		4.19

Notes: (1) We use the average weight of children between 0 and 10 years old as an instrument (adjusted for age and gender). In quadratic specifications, the square of the average weight of children is also included as an instrument. Note that IV regressions only concern households that have at least one child under 10 years old. Standard errors are robust at the household level. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (married or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and caste/religion. Level of statistical significance: 1 %***, 5 %**, and 10 %*.
Source: IHDS. Authors' calculations.

Table 8: Results from PSM analysis, INDIA.

		Underweight versus Others				Overweight/obese versus Others				Obese versus Others			
		Underweight	Others	Difference	T-stat	Overweight and obese	Others	Difference	T-stat	Obese	Others	Difference	T-stat
MEN													
All	Unmatched	0.102	0.400	-0.298***	-24.25	0.441	0.219	0.222***	29.75	0.432	0.273	0.159***	22.21
	ATT	0.102	0.182	-0.079***	-6.94	0.441	0.356	0.085***	18.88	0.432	0.377	0.055***	7.29
Urban	Unmatched	0.331	0.725	-0.395***	-13.34	0.660	0.521	0.139***	8.76	0.643	0.600	0.043***	3.00
	ATT	0.331	0.490	-0.491***	-5.92	0.660	0.570	0.089***	5.59	0.643	0.605	0.037**	2.56
Rural	Unmatched	0.050	0.237	-0.187***	-15.41	0.290	0.129	0.161***	20.67	0.287	0.156	0.131***	17.13
	ATT	0.050	0.103	-0.053***	-4.50	0.290	0.221	0.069***	8.58	0.287	0.227	0.060***	7.42
Manual workers	Unmatched	0.076	0.263	-0.187***	-17.23	0.303	0.148	0.155***	22.71	0.296	0.181	0.115***	17.26
	ATT	0.076	0.134	-0.059***	-5.53	0.303	0.236	0.067***	9.45	0.296	0.250	0.047***	6.63
Service workers	Unmatched	0.272	0.665	-0.393***	-7.15	0.575	0.489	0.087***	3.19	0.563	0.544	0.019	0.77
	ATT	0.272	0.463	-0.191***	-3.30	0.575	0.516	0.060**	2.04	0.563	0.537	0.029*	1.13
High-skilled workers	Unmatched	0.699	1.158	-0.460***	-5.21	1.142	0.965	0.176***	4.41	1.131	1.053	0.078**	2.25
	ATT	0.699	0.961	-0.263***	-3.04	1.142	1.041	0.100***	2.42	1.131	1.082	0.049*	1.37
WOMEN													
All	Unmatched	-0.267	-0.084	-0.183***	-14.48	0.015	-0.204	0.219***	21.50	0.018	-0.174	0.192***	17.72
	ATT	-0.267	-0.224	-0.043***	-3.76	0.015	-0.073	0.088***	7.70	0.018	0.056	0.073***	5.88
Urban	Unmatched	-0.073	0.229	-0.301***	-6.67	0.356	0.047	0.309***	10.88	0.369	0.110	0.259***	9.23
	ATT	-0.073	0.047	-0.119***	-2.87	0.356	0.201	0.155***	5.21	0.369	0.250	0.119***	3.92
Rural	Unmatched	-0.293	-0.189	-0.105***	-9.61	-0.159	-0.253	0.093***	9.81	-0.168	-0.238	0.070***	6.72
	ATT	-0.293	-0.264	-0.029***	-2.79	-0.159	-0.199	0.040***	3.89	-0.168	-0.195	0.026**	2.31
Manual workers	Unmatched	-0.289	-0.208	-0.081***	-8.22	-0.197	-0.257	0.060***	7.08	-0.212	-0.244	0.032***	3.47
	ATT	-0.289	-0.264	-0.026***	-2.64	-0.197	-0.220	0.024***	2.62	-0.212	-0.217	0.005	0.48
Service workers	Unmatched	-0.209	0.086	-0.295***	-5.27	0.217	-0.072	0.290***	7.99	0.247	-0.029	0.276***	7.60
	ATT	-0.209	-0.064	-0.145**	-2.53	0.217	0.069	0.178***	3.76	0.246	0.095	0.151***	3.78
High-skilled workers	Unmatched	0.200	0.720	-0.520***	-5.24	0.823	0.438	0.385***	6.92	0.824	0.542	0.282***	5.29
	ATT	0.209	0.417	-0.208**	-2.15	0.823	0.578	0.245**	4.08	0.824	0.647	0.177***	3.06

Notes: (1) ATT are mean-comparison tests where observations are weighted by propensity scores estimated by a Kernel algorithm. Propensity scores refer to the fitted probability of being treated (overweight or obese) versus non-treated conditional on the set of control variables. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (married or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and caste/religion.

Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: IHDS. Authors' calculations.

Table 9: Results from OLS regressions (log hourly wage in PPP US$), MEXICO.

	ALL			URBAN			RURAL			MANUAL WORKER			SERVICE WORKER			HIGH-SKILLED WORKER		
MEN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
BMI	0.009***	0.029*		0.011***	0.056**		0.006*	-0.007		0.014***	0.041*		-0.001	0.020		0.012**	0.011	
	(3.93)	(1.65)		(3.68)	(2.50)		(1.68)	(-0.22)		(4.57)	(1.65)		(-0.20)	(0.63)		(2.13)	(0.25)	
BMI squared		-0.000			-0.001**			0.000			-0.000			-0.000			0.000	
		(-1.17)			(-2.07)			(0.42)			(-1.09)			(-0.67)			(0.03)	
Overweight (25-30kg/m²)[1]			0.069***			0.096***			0.034			0.078**			0.049			0.042
			(2.89)			(3.19)			(0.92)			(2.44)			(1.20)			(0.63)
Obesity (>30kg/m²)[1]			0.080***			0.114***			0.032			0.133***			-0.007			0.099
			(2.82)			(3.12)			(0.73)			(3.40)			(-0.15)			(1.31)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,932	1,932	1,932	1,288	1,288	1,288	644	644	644	258	258	258	1,058	1,058	1,058	616	616	616
R-squared	0.351	0.351	0.351	0.332	0.332	0.332	0.368	0.369	0.368	0.209	0.209	0.212	0.125	0.125	0.125	0.303	0.304	0.304
WOMEN	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
BMI	-0.001	-0.015		-0.002	-0.009		0.001	-0.027		0.017**	0.035		-0.005	-0.018		-0.004	-0.040	
	(-0.47)	(-0.61)		(-0.51)	(-0.31)		(0.10)	(-0.66)		(2.09)	(0.52)		(-1.08)	(-0.49)		(-0.83)	(-1.07)	
BMI squared		0.000			0.000			0.000			-0.000			0.000			0.001	
		(0.56)			(0.25)			(0.68)			(-0.25)			(0.37)			(0.97)	
Overweight (25-30kg/m²)[1]			-0.003			-0.005			0.010			0.127			-0.005			-0.042
			(-0.09)			(-0.12)			(0.16)			(1.47)			(-0.11)			(-0.73)
Obesity (>30kg/m²)[1]			-0.021			-0.040			0.022			0.238**			-0.059			-0.071
			(-0.56)			(-0.87)			(0.33)			(2.22)			(-1.10)			(-1.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,932	1,932	1,932	1,288	1,288	1,288	644	644	644	258	258	258	1,058	1,058	1,058	616	616	616
R-squared	0.351	0.351	0.351	0.332	0.332	0.332	0.368	0.369	0.368	0.209	0.209	0.212	0.125	0.125	0.125	0.303	0.304	0.304

Notes: (1) Ref.=underweight and normal weight. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and ethnicity (Amerindian or not).
Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.
Source: MxFLS. Authors' calculations.

Table 10: Results from IV regressions, MEXICO.

	ALL		URBAN		RURAL		MANUAL WORKERS		SERVICE WORKERS		HIGH-SKILLED WORKERS	
MEN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BMI	0.031**	0.890*	0.018	1.620	0.046*	0.512	0.070***	0.359	-0.006	2.982	0.027	0.222
	(2.02)	(1.68)	(0.93)	(1.01)	(1.82)	(1.03)	(2.68)	(0.72)	(-0.28)	(0.89)	(0.77)	(0.17)
BMI squared		-0.015		-0.029		-0.008		-0.005		-0.053		-0.004
		(-1.62)		(-1.01)		(-0.93)		(-0.57)		(-0.90)		(-0.15)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,932	1,932	1,932	1,288	1,288	1,288	644	644	644	258	258	258
F-stat on excluded	78.38	40.10	48.44	24.23	29.07	15.25	26.35	14.13	52.92	27.98	13.20	7.84
instruments		38.38		23.05		14.49		13.55		26.99		7.05
WOMEN	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
BMI	0.039**	-0.327	0.043**	11.516	0.033	0.301	0.038*	0.540	0.041	2.067	0.039	-0.171
	(2.43)	(-0.43)	(2.27)	(0.12)	(1.05)	(0.67)	(1.87)	(0.90)	(1.43)	(0.41)	(1.52)	(-0.21)
BMI squared		0.006		-0.198		-0.005		-0.009		-0.036		0.004
		(0.48)		(-0.12)		(-0.62)		(-0.85)		(-0.40)		(0.26)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,932	1,932	1,932	1,288	1,288	1,288	644	644	644	258	258	258
F-stat on excluded	64.47	35.38	48.46	27.29	16.42	8.35	24.68	14.59	30.13	16.07	17.16	9.31
instruments		35.01		27.67		7.49		12.97		15.18		9.64

Notes: (1) We use the average weight of children between 0 and 10 years old as an instrument (adjusted for age and gender). In quadratic specifications, the square of the average weight of children is also included as an instrument. Note that IV regressions only concern households that have at least one child under 10 years old. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and ethnicity (Amerindian or not).

Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: MxFLS. Authors' calculations.

Table 11: Results from PSM analysis, MEXICO

		Overweight/obese versus Others				Obese versus Others			
		Overweight and obese	Others	Difference	T-stat	Obese	Others	Difference	T-stat
MEN									
All	Unmatched	1.004	0.824	0.180***	7.77	1.033	0.913	0.120***	4.71
	ATT	1.004	0.905	0.099***	3.67	1.033	0.987	0.046	1.71
Urban	Unmatched	1.115	0.920	0.196***	6.29	1.132	1.028	0.104***	3.22
	ATT	1.115	0.956	0.159***	4.53	1.132	1.081	0.052	1.49
Rural	Unmatched	0.850	0.731	0.119	3.5	0.887	0.780	0.107***	2.69
	ATT	0.850	0.843	0.006	0.16	0.887	0.867	0.020	0.48
Manual workers	Unmatched	0.857	0.717	0.140***	4.9	0.909	0.773	0.136	4
	ATT	0.857	0.744	0.112***	3.48	0.909	0.813	0.096***	2.69
Service workers	Unmatched	0.939	0.879	0.060	1.57	0.916	0.923	-0.007	-0.17
	ATT	0.939	0.893	0.046	1	0.916	0.955	-0.038	-0.92
High-skilled workers	Unmatched	1.656	1.490	0.165**	2.31	1.670	1.598	0.072	1.16
	ATT	1.656	1.692	-0.037	-0.41	1.670	1.618	0.052	0.8
WOMEN									
All	Unmatched	0.983	0.927	0.056	1.54	0.971	0.960	0.011	0.27
	ATT	0.983	0.980	0.003	0.08	0.971	0.986	-0.016	-0.39
Urban	Unmatched	1.044	1.002	0.042	0.96	1.033	1.029	0.004	0.09
	ATT	1.044	1.056	-0.012	-0.22	1.033	1.054	-0.021	-0.44
Rural	Unmatched	0.849	0.797	0.052	0.82	0.844	0.823	0.022	0.31
	ATT	0.849	0.822	0.027	0.35	0.844	0.825	0.019	0.26
Manual workers	Unmatched	0.621	0.462	0.159*	1.93	0.669	0.522	0.147*	1.67
	ATT	0.627	0.439	0.188**	2.02	0.669	0.521	0.148	1.47
Service workers	Unmatched	0.776	0.722	0.055	1.26	0.754	0.759	-0.005	-0.11
	ATT	0.776	0.795	-0.019	-0.36	0.754	0.806	-0.052	-1.11
High-skilled workers	Unmatched	1.514	1.431	0.084	1.43	1.521	1.469	0.052	0.8
	ATT	1.514	1.560	-0.045	-0.62	1.521	1.572	-0.051	-0.75

Notes: (1) ATT are mean-comparison tests where observations are weighted by propensity scores estimated by a Kernel algorithm. Propensity scores refer to the fitted probability of being treated (overweight or obese) versus non-treated conditional on the set of control variables. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and ethnicity (Amerindian or not).

Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: MxFLS. Authors' calculations.

Table 12: Impact of bodyweight on hours worked per week (OLS), CHINA.

	MEN				WOMEN			
	ALL	MANUAL WORKER	SERVICE WORKER	HIGH-SKILLED WORKER	ALL	MANUAL WORKER	SERVICE WORKER	HIGH-SKILLED WORKER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overweight (24-28kg/m²)[1]	1.989**	1.279	3.893***	1.427	0.310	-0.127	-0.094	1.760*
	(2.45)	(0.79)	(2.78)	(1.23)	(0.35)	(-0.05)	(-0.07)	(1.71)
Obesity (>28kg/m²)[1]	2.310**	2.204	3.019**	2.170	-1.081	-2.708	1.480	0.028
	(2.57)	(1.23)	(1.99)	(1.49)	(-0.80)	(-0.67)	(1.02)	(0.01)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,291	423	408	390	932	182	396	316
R-squared	0.062	0.075	0.057	0.077	0.131	0.139	0.121	0.110

Notes: (1) Ref.= Normal-weight. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill) and provincial dummies.

Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: CHNS. Authors' calculations.

Table 13: Impact of bodyweight on hours worked per week (OLS), INDIA.

	MEN				WOMEN			
	ALL	MANUAL WORKER	SERVICE WORKER	HIGH-SKILLED WORKER	ALL	MANUAL WORKER	SERVICE WORKER	HIGH-SKILLED WORKER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Underweight (<18kg/m²)[1]	-1.139***	-1.067***	-0.776	0.391	0.272	0.417	-0.441	0.458
	(-3.59)	(-3.20)	(-0.61)	(0.21)	(0.92)	(1.37)	(-0.36)	(0.25)
Overweight (25-30kg/m²)[1]	1.449***	1.507***	0.442	1.997*	-0.501	-0.545	-0.785	0.591
	(4.12)	(3.64)	(0.48)	(1.95)	(-1.19)	(-1.14)	(-0.67)	(0.45)
Obesity (>30kg/m²)[1]	2.008***	1.812***	1.921***	3.013***	1.204***	1.063***	1.815**	2.101**
	(9.64)	(7.86)	(3.14)	(3.80)	(4.16)	(3.31)	(2.16)	(2.15)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,311	25,920	4,651	2,740	14,836	11,666	1,969	1,201
R-squared	0.183	0.126	0.056	0.060	0.258	0.120	0.106	0.031

Notes: (1) Ref.= Normal-weight. (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (married or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and caste/religion.

Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: IHDS. Authors' calculations.

Table 14: Impact of bodyweight on hours worked per week (OLS), MEXICO.

	MEN				WOMEN			
	ALL	MANUAL WORKER	SERVICE WORKER	HIGH-SKILLED WORKER	ALL	MANUAL WORKER	SERVICE WORKER	HIGH-SKILLED WORKER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overweight (25-30kg/m²)[1]	0.706	0.258	1.872*	-0.254	-0.351	1.318	-0.729	-0.879
	(1.46)	(0.47)	(1.80)	(-0.14)	(-0.49)	(0.79)	(-0.73)	(-0.76)
Obesity (>30kg/m²)[1]	1.361**	0.146	2.395**	3.076	0.981	2.607	0.742	-0.221
	(2.41)	(0.21)	(2.17)	(1.61)	(1.27)	(1.52)	(0.69)	(-0.17)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,618	3,752	2,177	689	4,207	618	2,650	939
R-squared	0.049	0.045	0.047	0.054	0.030	0.100	0.024	0.056

Notes: (1) Ref.= Normal-weight; (2) Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), regional dummies and ethnicity (Amerindian or not).

Standard errors are robust at the household level. Level of statistical significance: 1 %***, 5 %**, and 10 %*.

Source: MxFLS. Authors' calculations.

Table 15: Oaxaca-Blinder decomposition for hourly wage.

		CHINA		INDIA		MEXICO	
		Men	Women	Men	Women	Men	Women
				Underweight versus Others			
All	Raw wage gap			0.298***	0.183***		
	Explained			0.228***	0.149***		
	Unexplained			0.070***	0.034***		
Manual workers	Raw wage gap			0.187***	0.081***		
	Explained			0.135***	0.059***		
	Unexplained			0.053***	0.022***		
Service workers	Raw wage gap			0.392***	0.295***		
	Explained			0.216***	0.190***		
	Unexplained			0.177***	0.105**		
High-skilled workers	Raw wage gap			0.460***	0.520***		
	Explained			0.227***	0.315***		
	Unexplained			0.233***	0.205**		
				Overweight and obese versus Others			
All	Raw wage gap	0.015	0.259***	-0.222***	-0.219***	-0.180***	-0.056
	Explained	-0.023	0.160***	-0.150***	-0.137***	-0.086***	-0.065**
	Unexplained	0.038	0.099**	-0.082***	-0.081***	-0.095***	0.008
Manual workers	Raw wage gap	-0.009	0.029	-0.155***	-0.060***	-0.140***	-0.159*
	Explained	-0.005	-0.016	-0.090***	-0.039***	-0.024	0.054
	Unexplained	-0.004	0.046	-0.065***	-0.021**	-0.115***	-0.213**
Service workers	Raw wage gap	0.113	0.292***	-0.087***	-0.290***	-0.060	-0.055
	Explained	0.039	0.094	-0.039**	-0.141***	-0.007	-0.068**
	Unexplained	0.074	0.198***	-0.048*	-0.148***	-0.054	0.013
High-skilled workers	Raw wage gap	0.014	0.166*	-0.176***	-0.385***	-0.165**	-0.084
	Explained	-0.012	0.019	-0.084***	-0.147***	-0.253***	-0.092*
	Unexplained	0.026	0.147*	-0.092**	-0.239***	0.088	0.008
				Obese versus Others			
All	Raw wage gap	0.093*	0.298***	-0.159***	-0.192***	-0.120***	-0.011
	Explained	0.025	0.180***	-0.110***	-0.130***	-0.082***	-0.027
	Unexplained	0.068	0.118*	-0.050***	-0.062***	-0.038	0.016
Manual workers	Raw wage gap	0.069	0.275	-0.115***	-0.032***	-0.136***	-0.147
	Explained	0.036	0.088	-0.067***	-0.026***	-0.042***	0.012
	Unexplained	0.033	0.187	-0.048***	-0.006	-0.094***	-0.159
Service workers	Raw wage gap	0.159*	0.311***	-0.019	-0.276***	0.007	0.005
	Explained	-0.001	0.107	0.012	-0.138***	-0.037**	-0.043**
	Unexplained	0.160	0.204**	-0.031	-0.138***	0.044	0.048
High-skilled workers	Raw wage gap	0.080	0.166	-0.078**	-0.282***	-0.072	-0.052
	Explained	0.057	0.050	-0.031*	-0.091***	0.000	-0.108***
	Unexplained	0.023	0.116	-0.047	-0.180***	-0.073	0.056

Notes: Control variables are: age, squared age, highest completed education level (none, primary, lower secondary, upper secondary or tertiary), marital status (in a couple/married or not), number of children, location (rural or urban), occupation type (manual, service, high-skill), country-specific regional dummies and caste or ethnic origins (only for India and Mexico).
Level of statistical significance: 1 %***, 5 %**, and 10 %*.
Source: CHNS, IHDS and MxFLS. Authors' calculations.