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A. Deeva[1]

Earnings and overweight in Russia: Men and women

This paper investigates the influence of Body-Mass-Index (BMI) on the earnings of men and women. The aim is to identify weight — wage discrimination in the Russian labour market, which results in overweight and obese people earning significantly less than normal-weight workers. The study is conducted using a panel dataset from the Russian Longitudinal Monitoring Survey (RLMS–HSE), collected by HSE University, which covers individuals from 2013 to 2023, and Rosstat regional-level data for the corresponding years. Based on the results, we can conclude that being overweight leads to a decrease in wages for female employees, but does not appear to affect the wages of male employees. The industry of occupation plays a role in determining the presence and degree of wage reduction of overweight women in Russia. The largest earnings penalty due to extra weight is found for women employed in construction, education, trade, and consumer services industries. The size of the earnings reduction, following a one-point increase in BMI, varies from 3 to 9%. In industries such as transportation, agriculture, management, finance, and the energy sector, no sign of a weight–wage association is detected.

Keywords: obesity; endogeneity; instrumental variables method; heteroscedastic errors; industry.
JEL classification: C36; I12; J31; J16.

1. Introduction

In recent decades, the prevalence of obesity has become an epidemic and is associated with an increasing number of chronic diseases and higher mortality rates both in Russia (Savina et al., 2022; Balanova et al., 2018; Martinchik et al., 2021) and worldwide[2], negatively affecting the overall wellness of the population. Another important adverse aspect of obesity concerns the social life of individuals with extra weight and is called weight discrimination or fatphobia. Weight discrimination leads to biased evaluations of overweight students' performance at school (Dian, Triventi, 2021; Glock, Schuchart, 2021), worse quality of medical treatment (Phelan et al., 2015; Puhl, Brownell, 2002), and problems in the labour market. Overweight people have a lower chance of being employed and earn less based only on their weight, while the gender of individual and the type occupation are also significant factors in determining the weight–wage relationship (Flint et al., 2016; Roehling et al., 2007; Lin, 2016; Baum, Ford, 2004; Cawley, 2004).

[1] **Deeva, Anastasiia** — HSE University, Moscow; asgolubtsova@hse.ru.

[2] See https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight.

Research has revealed that individuals with low socio-economic status and low income tend to consume products with high caloric density and to overeat, leading to obesity (Briers, Laporte, 2013; Kpelitse et al., 2014). Here, reverse causality arises: on the one hand, individuals with upper-normal weight due to wage discrimination may have lower earnings, and, on the other hand, people with lower income tend to have a higher probability of being overweight. In this paper, by discrimination we mean weight–wage discrimination, so that equally-productive workers may receive lower wages based only on their weight. The reverse causality problem, augmented with variable omission, may cause potential endogeneity, which should be accounted for.

To remove potential endogeneity in the regression of the natural logarithm of earnings on Body-Mass-Index (BMI), the instrumental variables approach was used (Lewbel, 2012). Lewbel's heteroskedasticity-based instrument can be applied when two conditions are met. Firstly, there should be no available strong exogenous instrument, which is the case for BMI as an instrumented variable. Secondly, some assumptions proposed by Lewbel must hold, relying on tests and economic rationale. The core idea lies in using the property of heteroskedasticity of residuals in the BMI equation on its exogenous determinants to construct an artificial instrument for BMI. After the instrument for BMI is obtained, we perform a standard Two-Stage Least Squares (TSLS) estimation, where at the second step we obtain a consistent estimate of the BMI coefficient.

The research uses a panel dataset of the Russian Longitudinal Monitoring Survey conducted by HSE University (RLMS–HSE) for the years 2013 to 2023. The dataset includes 11 waves of yearly data, in the form of representative samples, on individuals who participated in the survey either once or multiple times. In addition, the regional-level data from Rosstat statistical compendium '*Regiony Rossii: sotsial'no-ekonomicheskie pokazateli, 2024*' was used.

The literature highlights findings in the field of socio-economic consequences of obesity and weight discrimination obtained on Western, predominantly American, data. Despite its high social importance, this topic has been poorly explored in the Russian economic literature.

This paper contributes in the following way. Firstly, an econometric analysis was conducted on Russian data at the individual gender-specific level. It was found that female earnings decrease by around 4% with each extra BMI point. For men, no significant relationship between earnings and BMI is detected. Secondly, the role of the type of occupation in determining the association between wages and BMI on Russian data is studied, which is done for the first time in the literature.

2. Literature review

To understand how weight discrimination works in the labour market, we need to go deeper into the underlying social context. Compared to all other types of discrimination (race, gender, age), weight discrimination is explained by social and psychological reasons rather than purely physical characteristics. Overweight people are judged for the underlying social misperceptions and norms, which make us think that obesity is a signal of laziness or weak willpower. While the prevalence of weight discrimination is higher than one might suggest, the reported rates of weight discrimination in the US are close to the rates of racial discrimination, especially among women (Puhl et al., 2008).

Unlike other forms of discrimination, we treat overweight people differently not because of what they look like, but because of who we think they are. That is why weight discrimination is so damaging for overweight people: they are seen as psychologically defective. This misconception affects every aspect of the lives of people who are overweight, from their families to employers, who automatically assume that obesity means low productivity and low motivation.

As a result, overweight people may feel socially excluded, leading them to deeper complexes, overeating, worse performance at school, university, and work. So, at some point it becomes extremely difficult to break this infinite spiral, since the first thing an overweight person should do is to make society treat them as a normal weight person (Wang, 2008).

Previously, the problem of obesity was most prevalent in developing countries among people with high socio-economic status, so it was not considered an epidemic. While the trend has reversed in recent years, the more a country's gross national product grows, the greater the shift in the burden of obesity towards people with lower socio-economic status (Monteiro et al., 2005).

One of the ways to analyse the connection between BMI, income, health, and life satisfaction is to use piecewise regressions. Hübler (2019) constructs Lewbel's instrument for BMI to break endogeneity in income regression. Based on a panel dataset of German households for the years 2006–2016, it was found that under-weight women receive wages, which are larger than the ones earned by normal-weight women and women with upper-normal values of BMI. For men the results are the opposite: normal-weight men have earnings, which are significantly higher than for the representatives of other weight groups. It was also detected that obese people, as more irresponsible, enjoy life more than other people and, so, despite social and health problems show higher levels of life satisfaction (Hübler, 2019).

Other research estimates the influence of obesity on happiness using an instrumental variables approach. Results indicate that in Germany, UK, and Australia obesity and the subjective well-being of individuals are negatively correlated. First lags of BMI are used as instruments. However, such an instrument may be unreliable since it is correlated with the error term and is not exogenous. Matching methods are not employed and BMI itself is incorporated into the regression as a linear term causing endogeneity (Katsaiti, 2012).

In research conducted on 13 waves of the US pooled data (from 1981 to 2000) collected by The National Longitudinal Survey of Youth (NLSY), three approaches to estimate weight–wage regression are used. One of these approaches, similarly to the one used in (Katsaiti, 2012), chooses the lag of weight as an instrument for current weight in order to prevent the simultaneous effect of wages on weight and vice versa during the same period. Two other approaches are fixed-effects estimation, which allows the removal of the effect of time-invariant unobserved characteristics on weight and earnings, and the method of instrumental variables. The only estimation result, which is consistent across all three applied methods, is the negative influence of White women's weight on their wages, while for women of other races considered (Black, Hispanic) and for men the results are ambiguous (Cawley, 2004).

Another paper dedicated to the investigation of BMI effect on wages based on NLSY data uses a panel sample for 1979 to 1998. The four estimation strategies are applied, with the core idea lying in the use of fixed effects specifications to control for unobserved heterogeneity at the individual level. The results show that obesity reduces monthly earnings of both male and female respondents, with twice the wage penalty for women. On average, the increase of BMI by one point leads to a 3% wage reduction for men and to a 6% cut for women (Baum, Ford, 2004).

An earlier paper based on two waves (1981 and 1988) of NLSY data traces the effect of BMI on the socio-economic status of individuals on labour market and marriage market outcomes. It is detected that obese women suffer from large family income deficits compared to women with normal weight. Such a gap in family incomes of women from different weight groups arises from adverse labour and, especially, marriage market conditions for overweight women. For men no consistent evidence across models and samples on wage cuts connected with obesity is found (Averett, Korenman, 1996).

Other instruments used to remove endogeneity for BMI include a paper exploiting a mother's obesity and sibling's BMI as instruments for an individual's BMI. However, such instruments may be endogenous, because of unobserved cultural or psychological factors, which will have an impact on the weight parameters of the whole family (Sabia, 2007).

The quantitative study analyses cross-sectional data for 2008, collected by the Panel Study of Family Dynamics of Taiwan. To resolve potential endogeneity between monthly wages and BMI, the TSLS approach is applied with two instruments used. The first instrument is the number of fast-food restaurants in the area where a respondent lives, since the more widespread fast-food chains are the higher junk food consumption and subsequent weight gain is. The second instrument is the prevalence of obesity where the respondent lives, as this is associated with the peer group effect. The peer group effect means that there is some environmental influence, such as behaviours and social norms of peers, which affects the food behaviour of all residents in the area. The estimation results show that one point increase in BMI leads to a 7.4% monthly wage cut. When the effect of BMI on wages is studied for male and female sub-samples separately, it is found that, for women, the corresponding wage penalty for extra weight is larger than for the mixed-gender sample (10.1 vs 7.4%), while for men the result is statistically insignificant. When the sample is split into two groups subject to the type of occupation, where the first fields are managerial, sales, and services occupations, and the other refers to the blue-collar occupations, it is detected that the increase in BMI leads to earnings reduction only for employees involved in service sectors. A one point increase in BMI is followed by an average reduction of earnings by 9.8% for people with managerial, sales, and services occupations (Lin, 2016).

Studies investigating industry-specific wage and employment effects for overweight employees are scarce, controversial and predominantly descriptive. There is evidence that overweight individuals applying for positions in the fitness industry have lower chances of being employed compared to their normal-weight counterparts (Sartore, Cunningham, 2007). A similar tendency is observed for manual and heavy manual occupations, where the more physically demanding the job is the smaller the probability of an overweight individual of getting this position. Obese women are found the least suitable for manual and heavy manual occupations (Flint et al., 2016). There are indications of weight-based discrimination of women in the airline industry (Lynch, 1996), and also more negative customer evaluations of overweight employees in the retail industry and of the organisation at which these employees work (Ruggs et al., 2015). While in a previously mentioned paper on NLSY data, no larger wage penalty for obese individuals involved in customer-oriented occupations compared to other fields is detected (Baum, Ford, 2004).

A review of the literature reveals that wages may affect BMI in developed countries. Individuals from low-income groups are more likely to engage in overeating, leading to higher rates of being overweight and obesity compared to those from middle- and high-income groups. A survey based on a sample of 1156 adults from low-income communities in New York, demonstrates that individuals in low-income areas tend to use menu labels less frequently than those in higher income areas. When calorie information, allowing to decrease meal density, is available low-income individuals usually ignore it (Elbel et al., 2009). The application of instrumental variable quantile regressions to the data from a Canadian Community Health Survey for the years 2000–2009, with 316270 unique individuals, helped to discover that the higher the household incomes, the lower the probability of obesity and the lower are respondents' values of BMI. The relationship is strongest for female survey participants (Kpelitse et al., 2014).

A qualitative survey, conducted in 2011 on a sample of 105 respondents from New York, investigates individual and environmental factors affecting the choice of the food buyers. The target population group are representatives of socio-economic minorities with low incomes, where 92% of them are either Latinos or African-Americans. The study shows that for low-income people there appear to be some factors which are more important to them than the problems of being overweight and obesity. When menus in fast-food chains are labelled, they can be either misinterpreted or ignored, while in some cases the calorie information disclosure is followed by the increase in the number of calories consumed (Schindler et al., 2013).

Research conducted in the form of 5 experimental studies reveals that money and food are very close substitutes. Financial dissatisfaction makes individuals compensate with food consumption of higher caloric density and/or bigger portions, possibly leading to obesity in the long-run (Briers, Laporte, 2013).

Very few papers highlighting the problem of being overweight and its socio-economic consequences have been done based on Russian population data. These studies show an ambiguous relationship between individual earnings and being overweight. The results of a regression analysis performed on the RLMS–HSE data for the years 2012–2016 show a concave relationship between male wages and BMI and no association between female earnings and BMI (Kolosnitsyna, Kulikova, 2018). While the results of regression models estimation on the RLMS–HSE data for 2006 demonstrate that there exists a positive relationship between male earnings and BMI and, again, no link between these two variables for women (Kolosnitsyna, Berdnikova, 2009). In both studies, a potential simultaneous dependence between earnings and BMI, which could alter the results obtained, is not taken into account.

An analysis of Russian data, collected by the Levada-Center for HSE for 2011 and 2017, depicts that over those six years, the average BMI of Russians increased, and for women this increase is bigger. A negative relationship between female earnings and BMI was detected, which may signal either weight–wage discrimination or the lower productivity of overweight workers. In terms of drawbacks, this paper does not provide a regression analysis, thus, the influence of other factors aside from BMI (e. g., education) on earnings is not controlled and no quantitative effect is traced (Aleksandrova, Kolosnitsyna, 2018).

Overall, it is expected that in developed countries citizens with lower incomes will have higher values of BMI. At the same time, overweight people are more vulnerable to discrimination in the labour market and may earn less. This gives rise to a reverse causality problem and creates potential endogeneity that should be addressed. In addition, the exact pattern of weight–wage discrimination may crucially alter with the gender of an employee and the industry of occupation.

Based on the results of previous studies we test the following hypothesis in this paper:

The effect of individual's BMI on individual earnings may be different depending on the gender of employees in the Russian labour market.

3. Data description

This research is performed on RLMS–HSE panel dataset[3]. The panel data are a repeated sample of individuals with a split panel for the years 2013–2023.

[3] See http://www.hse.ru/rlms.

Sample selection criteria are that we include only those individuals of working age (16 and over) and have an officially paid job. The panel dataset after data processing includes 55648 observations with 12456 unique individuals, and the panel is unbalanced.

Regional-level data is obtained from Rosstat statistical compendium ‘*Regiony Rossii: sotsial’no-ekonomicheskie pokazateli, 2024*’[4]. The two regional-level variables are CPI in a region and regional healthcare per capita expenditures.

For the purposes of this research we choose the following individual characteristics: monthly earnings, BMI, age, gender, level of education, marital status, and number of children. The job characteristics are the intensity of work and the type of industry. We also control for the type of settlement where a respondent lives and for the level of medical care in the region where a respondent lives.

Using these individual characteristics we form the variables of interest. The dependent variable is the natural logarithm of earnings (*log_earnings*), where earnings denote real monthly after-tax wages received at the main official job, and measured in rubles as for 2023 prices. To find the value of real earnings, we use the most recent year (2023) as the base year and inflate the value of earnings for all previous years by the multiple of regional CPI. CPI in a region is calculated in December of the current year to December of the previous year (taken as 100%) in percentage points.

The list of regressors, which are also further used in the model description and regression estimates, is as follows. The main explanatory variable is BMI, which is calculated as weight divided by squared height and multiplied by 10000, where weight is the individual’s weight reported in kilograms and height is reported in centimetres. With respect to BMI, an individual is under-weight if their BMI < 18.5, normal-weight if $18.5 \leq$ BMI < 25, overweight if $25 \leq$ BMI < 30 and obese if BMI ≥ 30.

The gender of an individual is presented via the dummy *male,* where *male* equals to 1 if the respondent is a man and to 0 if it is a woman. The variable *age* denotes the actual age of the individual in years on the date of the survey, and age^2 is the squared value of age of a person, divided by 100. The level of education of the individual is taken into account with a dummy variable *education*, which equals to 1 if the respondent has either vocational secondary education diploma or higher education diploma, and to 0 if the respondent has finished the secondary school educational level or lower level of education. The variables *reg_ctr* and *town* are dummies, indicating the administrative status of an individual’s place of living (place of living): *reg_ctr* equals one if a person lives in the regional centre and zero otherwise, *town* equals 1 if a person lives in a town (not the regional centre). The base category for this group of dummies are small settlements. The variable *married* is a dummy, which indicates whether a respondent is officially married or cohabiting. The variable *children* stands for the number of children (below 18 years old) the respondent has. The variable *log_hours* indicates intensity of work and is calculated as the natural logarithm of hours worked at the main official job within the last month. The variable *exp_p_cap* stands for yearly regional healthcare per capita expenditures (health care expenditures of consolidated budgets of the subjects of the Russian Federation) as for 2023 prices, and approximates the level of medical care in the region where a respondent lives.

The type of industry is formed as a group of dummy variables *industry_j*, where *j* takes the values from 1 to 10. The following 10 industries, ordered from 1 to 10, are distinguished: construction,

[4] See https://www.rosstat.gov.ru/folder/210/document/13204.

transportation and communication, agriculture, management, education, healthcare, trade and consumer services, finance, energy industry, and others. The base industry is manufacturing.

The year of the survey is introduced with a group of dummies named *year_k*, where *k* stands for a particular year studied and varies from 2014 to 2023. The base year is 2013 and the dummy *year_2013* is omitted to prevent the problem of perfect multicollinearity, resulting from the dummy trap.

The descriptive statistics of individual characteristics for our sample can be found in Table 1.

Table 1. Descriptive statistics of individual characteristics

Total number of observations	55648
Total number of individuals	12456
Average age (years)	45
Average BMI	26.84
Average earnings (rubles/month, in 2023 prices)	40117
Average number of hours worked (hours/month)	176
Average number of children individuals have	1
Share of men, %	44
Share of women, %	56
Share of married or co-living individuals, %	80
Share of individuals with unfinished secondary education, %	8
Share of individuals with secondary school diploma, %	31
Share of individuals with vocational secondary education diploma, %	27
Share of individuals with higher education diploma and more, %	34
Share of individuals from small settlements, %	28
Share of individuals from towns (not regional centre), %	31
Share of individuals from regional centres, %	41

Source: RLMS–HSE 2013–2023, working population with official job, aged 16+.

There are many factors which may potentially affect an individual's earnings. In this paper we investigate how earnings vary with gender, age, level of education, place of living, intensity of work, industry of occupation, family status, parental status and BMI. In Figure 1 we can observe how the average earnings of respondents change with their age and gender.

As depicted in Fig. 1, on average female earnings are considerably lower than male, with approximately a 40% margin. The largest average earnings of around 54000 rubles monthly are earned by men from 35 to 44 years, and the smallest amounts are earned by women below 25 years. For both genders the relationship between average labour income and age is concave, whereas before the age of 35–44 years earnings are growing as the age of respondent is increasing, but after that age they start decreasing. For women this relationship is smoother than for men, with a lower discrepancy in earnings between different age groups. We may also note that the gap in male and female earnings is reducing when workers get closer to their retirement age. To find out how the wages of men and women and their intensity of work are affected by educational level and place of living, one should turn to Table 2 below.

The data in Table 2 reveals several patterns in earnings distribution. Firstly, as already observed in Fig. 1, earnings of respondents strongly depend on their gender, where men consistently earn

Fig. 1. Age–earnings profiles (rubles, 2023 prices) for males and females, 2013–2023

higher wages than women across all categories. Secondly, urban residency correlates with a higher level of earnings, where average earnings monotonically increase with the size of an individual's place of living across both genders and both educational levels. Thirdly, higher educational attainment is associated with larger salaries regardless of the type of residency and gender, with an approximately 35% wage premia for higher or vocationally educated women living in small settlements and towns, 25% premia for men living in small settlements and towns, and a 40% premia for employees from regional centres. In general, the most extreme, almost triple, gap in earnings is detected between vocational/higher-educated men living in regional centres (average wage for this group is around 64241 rubles) and less-educated women living in small settlements

Table 2. Distribution of average monthly earnings and work intensity across individuals with different educational levels and different places of living

Level of education	Place of living	Gender	Average earnings, rubles	Intensity of work, hours per month	Share of individuals, %
Completed secondary education or lower	Small settlements	Women	23203	173	6
		Men	35824	195	8
	Town	Women	24814	171	5
		Men	39973	187	7
	Regional centres	Women	30413	171	7
		Men	46069	189	8
Completed secondary vocational or higher education	Small settlements	Women	31004	165	10
		Men	43411	186	5
	Town	Women	34367	164	12
		Men	50092	180	7
	Regional centres	Women	42662	165	16
		Men	64241	183	11

Note. Earnings are measured in rubles in prices of 2023.

(average wage is around 23203 rubles). As for work intensity, it shows a negligible variation across all regarded groups, though men report marginally longer working hours than women.

Another crucial factor, which can explain the variation in earnings, is the industry of occupation. The data in Table 3 highlights a persistent gender–wage gap, with men earning substantially more than women in all sectors — most starkly in finance (85860 vs. 43045 rubles) and trade & consumer services (49065 vs. 32730 rubles). Notably, education is the only sector with an almost wage parity for male and female employees (29993 vs. 30370 rubles), yet women dominate its workforce (10.19 vs. 1.40% male representation). Highly masculinized industries like construction (5.70 men vs. 1.23% women) and transportation (6.55 vs. 2.77%) exhibit both higher male wages and participation, whereas female-dominated field such as healthcare (7.25 vs. 1.03%) shows narrower but persistent pay gap. The main gender–industry pattern is that women are predominantly concentrated in lower-paid service sectors (education, healthcare, and trade), while men in technical high-wage sectors (manufacturing, construction, and transportation).

Table 3. Distribution of average monthly earnings across industries of occupation

Industry	Average earnings, rubles		Share of respondents occupied, %		
	Women	Men	Women	Men	Total
Manufacturing	35175	50059	7.60	10.61	18.21
Construction	46642	53525	1.23	5.70	6.93
Transportation	35542	49926	2.77	6.55	9.32
Agriculture	24835	32355	1.21	2.22	3.44
Management	31269	41803	2.10	0.66	2.76
Education	30370	29993	10.19	1.40	11.59
Healthcare	33795	40175	7.25	1.03	8.28
Trade & consumer services	32730	49065	13.23	6.44	19.68
Finance	43045	85860	1.48	0.55	2.04
Energy industry	39602	48089	0.68	1.47	2.14
Other industries	35335	45983	7.89	7.73	15.61

Note. Earnings are measured in rubles in prices of 2023.

Table 4 illustrates how monthly earnings are distributed among s men and women with different family statuses. The majority of our sample are married (officially or cohabiting) individuals, who have at least one child, their share is 50%. For males, the main factor determining difference in wages is fatherhood, where men who have children earn more than men without children (approximately 53000 rubles versus 40000 rubles for married men and 41000 rubles versus 35000 for single men). The presence of a spouse affects male wages positively. The largest earnings are gained by married men with children, the lowest by single men without children. For females, the main determinant in terms of family status is presence of children similarly to men, so that women with children receive higher wages than those without children regardless of marital status. The fact of marriage has a mixed effect on female labour income where the difference in earnings of married and single women is too small and most likely statistically insignificant.

Another factor potentially affecting respondents' earnings is their body mass index. Figure 2 shows that the relationship between BMI and real monthly earnings differs drastically for men

Table 4. Average monthly earnings subject to marital and parental statuses of society

	Married or co-living				Unmarried and single			
	Has children		No children		Has children		No children	
	Female	Male	Female	Male	Female	Male	Female	Male
Average earnings, rubles	34860	53297	31918	40254	37521	41030	31882	35479
Share of sample, %	23	27	16	14	6	1	11	1

Note. Earnings are measured in rubles as in prices of 2023.

and women. A negative trend is observed between female earnings and BMI: the highest wages are gained by underweight and normal-weight women, the lowest — by overweight and obese women. On the contrary, the relationship between earnings and BMI is positive for men, where the smallest wages are received by underweight men and the largest ones are grasped by obese men. However, these relationships may be also partially explained by the interaction of BMI and earnings with other factors that are not visible on the graph. That is why a more detailed econometric analysis is needed to investigate the exact pattern of BMI and earnings interaction for the two genders.

After discussing the main determinants of earnings, we turn to the analysis of BMI sample structure and BMI determinants. As depicted in Fig. 3, the two prevailing weight groups in our sample are normal-weight individuals (around 39% of the total sample) and overweight individuals (around 36% of the total sample). Normal weight is more common among women (41 vs. 36%), while overweight is more prevalent among men (42 vs. 31%). Obese respondents constitute around 23% of our sample with women suffering from obesity more frequently than men. The rates of overweight and obesity found on our data sample stand very close to the ones found by researchers on the dataset from selective monitoring of the health status of the population by Rosstat in 2021 (Churilova, Rodina, 2024). Only 1–2% of respondents are underweight, so, in further statistical analysis, they are attributed to the normal-weight group (BMI < 25). Slightly more than one half of individuals are overweight and obese, and the other half consists of normal-weight employees, meaning that the sample is balanced with respect to major weight groups.

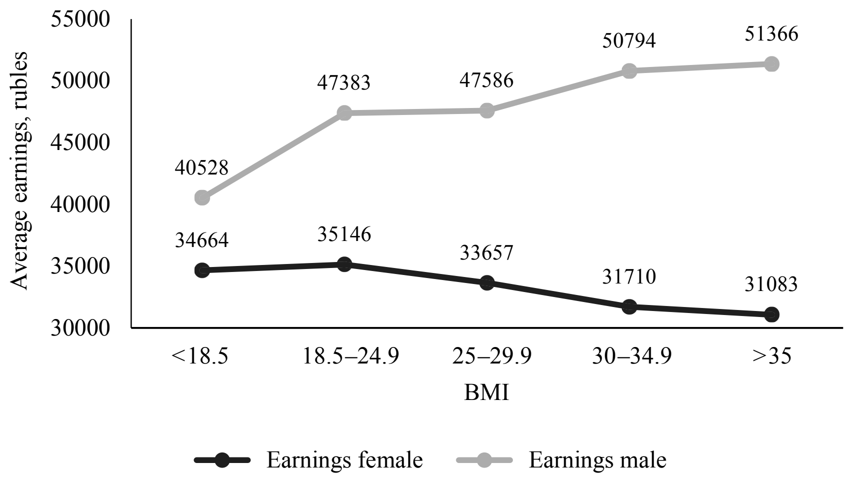

Fig. 2. The link between BMI and average monthly earnings (rubles, 2023 prices)

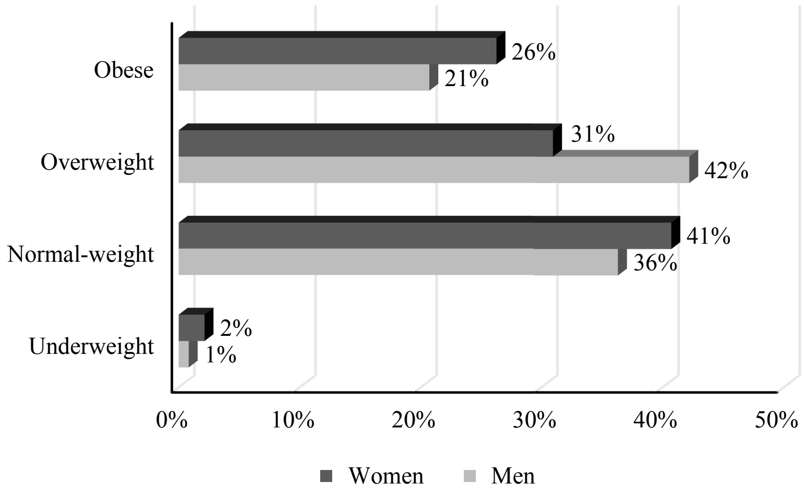

Fig. 3. Distribution of respondents across weight groups, %

When we study the BMI structure of the sample, it is worthy to account for such main drivers of BMI as gender and age. Figure 4 shows that the BMI of men and women monotonically increases with age, though the gradient appears steeper for men than for women after middle age. Before the age of 30, on average, the respondents are normal-weight regardless of their gender, where male BMI is higher than the female one. Starting from the age of 30, the average individual tends to be overweight, but the female BMI is still smaller than the male one. The age of 40–49 can be regarded as the inflection point, with male and female BMI being around 27 points. When the age of 50 is reached, the risk of obesity increases sharply over time for women and, in contrast, stays rather stable for men. Women in the age cohorts of 50 years and older, on average, are more overweight than men, with extremely high values of the BMI to be found for women more frequently than for men.

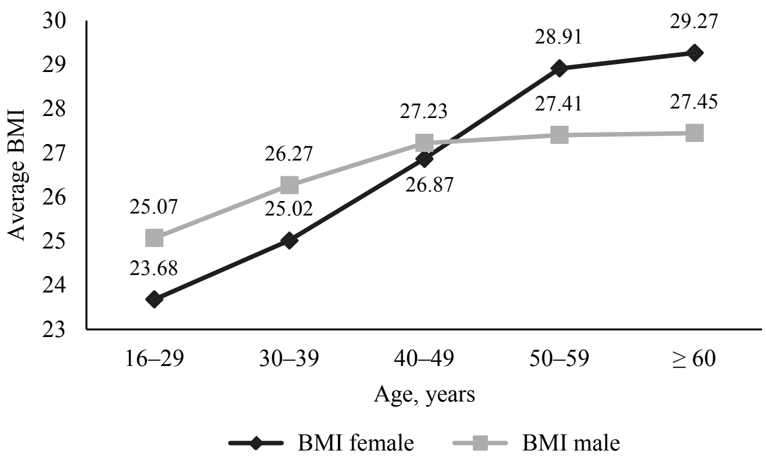

Fig. 4. Body Mass Index subject to age–gender structure of the sample

The BMI may diverge across individuals in terms of their place of residence and educational level. In Table 5, the distribution of weight groups subject to the place of living of men and women is depicted. Table 6 provides the BMI structure of the working population depending on the level of education. Our findings on the link between the prevalence of overweight and obesity and the two listed above socio-economic factors correspond to the results of earlier studies on representative Russian data samples (Martinchik et al., 2021; Balanova et al., 2018).

Table 5. Distribution of respondents from different places of living across weight groups, %

Weight group	Place of living								
	Small settlements			Town			Regional centre		
	Women	Men	Total	Women	Men	Total	Women	Men	Total
Normal-weight	37	33	35	44	37	41	46	40	43
Overweight	31	43	36	32	44	37	30	40	35
Obese	32	24	28	24	19	22	24	20	22

Table 5 shows that the place of living can be an important predictor of the BMI structure. The highest proportion of normal-weight individuals (43%) live in regional centres and the lowest one in small settlements (35%). This pattern is consistent for both genders, though the prevalence of normal-weight women is by 4–7% larger regardless of the place of living. The share of overweight individuals is stable with the proportion of overweight men exceeding that of women by 10% across all three types of residence. The problem of obesity is most common in small settlements and among women, where every third woman in rural areas, on average, suffers from obesity. In general, the share of normal-weight individuals increases from small settlements to towns and from towns to regional centres, and the share of obese individuals grows from rural to urban areas. Such a trend can be partially explained by a higher level of education and a higher level of wages of workers in towns and regional centres, which affects eating behaviour and food choice.

Table 6. Distribution of respondents with different educational levels across weight groups, %

Weight group	Level of education					
	Finished secondary education or lower			Finished secondary vocational or higher education		
	Women	Men	Total	Women	Men	Total
Normal-weight	39	38	38	45	36	42
Overweight	30	42	37	31	42	35
Obese	31	20	25	24	22	23

As in Table 6, the BMI structure of the working population is contingent on the educational level. The share of normal-weight individuals increases with the level of education (from 38 to 42%), where normal weight is most widespread among women with higher education (45%). The share of overweight is stable both for men and women across the two levels of education regarded, with prevalence of overweight being slightly higher among the respondents with finished secondary education level or lower. While the rates of obesity are higher, the lower is the level of education, where women with a finished secondary level of education or lower are the group at the highest risk of obesity (31%). Such results may be explained by the fact that people with higher education are better informed and care more about their health and, as a result, the food they consume (Elbel et al., 2009; Schindler et al., 2013). While the smallest rate of obesity (20%) is found among men with a comparatively low level of education, which may be connected with their more frequent involvement in hard physical or manual labour, leading to higher level of physical activity and calorie use.

The descriptive analysis of the data depicts that the monthly wage of an employee ranges across different factors such as gender, age, level of education, place of living, industry, family status, and BMI. The variation in the BMI can also be attributed to some of the above-mentioned parameters. Regarding the link between monthly earnings and the BMI, it can be preliminary inferred that overweight and obese women may face some wage penalty, while obese men, conversely, may experience wage premia. However, the exact relation is hard to be traced at this stage of analysis. More detailed econometric analysis is provided in the next sections.

4. Methodology and model specification

In this paper, we estimate the models investigating the relationship between an individual's earnings and BMI. This is a variation of the Mincer equation (Mincer, 1958). In the models, the dependent variable is the natural logarithm of earnings, and the main explanatory variable of interest is the BMI. We control for such factors as age, education level, place of living, marital status, number of children, intensity of work and industry of occupation.

When examining the relationship between an individual's earnings and BMI, two potential econometric problems, causing endogeneity, should be taken into account. The first is reverse causality, as the relationship between earnings and BMI can be represented as a system of simultaneous equations, where BMI affects earnings and earnings affect BMI. The second issue is the omitted variables problem. Firstly, we need all our regressors for *BMI* and *earnings* to be exogenous to prevent violation of Gauss–Markov assumptions (otherwise, inconsistency occurs). Only a tight range of explanatory variables can be used. Secondly, the surveys do not always contain all required data for such research due to its specificity and narrow implementation, and the RLMS–HSE database used in this paper is not an exception.

In order to combat occurring endogeneity, an instrumental variables (IV) approach is used as an instrument for endogenous BMI. Previous studies show a lack of sufficiently strong and reliable exogenous instruments for BMI. This paper applies Lewbel's artificially constructed heteroskedasticity based instrument (Lewbel, 2012).

Lewbel's heteroskedasticity based instrument can be used when two conditions desirably hold. First, strong exogenous instruments should not be available, otherwise a classical IV approach is preferable. Second, the three assumptions proposed by Lewbel should hold, if not theoretically, then at least empirically, based on tests and economic rationale (Lewbel, 2012).

Assumption 1 is empirically untestable, still holding theoretically, because there exists some set of unobserved personal characteristics (willpower, motivation, and intelligence), which influences both *BMI* and *earnings* simultaneously. Assumption 2 is only partially empirically testable and does not necessarily hold for our data (Baum, Lewbel, 2019). While if no crucial variables are omitted and the model is correctly specified then assumption 2 should hold theoretically. For panel data, Assumption 3 is tested with the Wald test for fixed-effects models to detect groupwise heteroskedasticity, and it holds empirically. Additionally, the *J*-test is performed and assumption of regressors' exogeneity is not violated for any model.

The core methodological idea lies in using the property of the heteroskedasticity of residuals in *BMI* regression on its exogenous determinants to construct an artificial instrument for *BMI*. After the instrument for BMI is obtained, we perform standard Two-Stage Least Squares (TSLS) estimation, which helps give consistent valid estimates in the *earnings* equation and cure the model of endogeneity.

We denote the list of exogenous regressors (with controls) for *BMI* as *X*. Set *X* includes basic socio-demographic factors, level of medical care and time dummies which are naturally exogenous, because they cannot be affected by individuals themselves in most cases. Additionally, the set includes job characteristics. Then subset *Z* is selected from *X*[5], where *Z* includes only those exogenous regressors of *BMI*, which are used to construct an artificial instrument. The variable *gender* is excluded from *X* and *Z*, when estimating models on male and female subsamples.

$$X = [age,\ age^2,\ gender,\ level\ of\ education,\ marital\ status,\ children,\ place\ of\ living,\ level\ of\ medical\ care,\ intensity\ of\ work,\ working\ industry,\ year\ of\ survey], \quad (1)$$

$$Z = [age,\ age^2,\ gender,\ level\ of\ medical\ care]. \quad (2)$$

The variables *age*, age^2, *gender* can definitely explain heterogeneity in *BMI*, since they are physical parameters, exogenous by their origin, which affect weight strongly. As observed in Fig. 4, weight tends to increase with age and depends on gender. The *level of medical care* in the region may affect individual's health and BMI, while being an exogenous parameter set by policy-makers. That is why these variables can be used to construct a reliable instrument.

As for other variables from *X*, their effect on the *BMI* is not that straightforward, and their coefficients are found to be predominantly insignificant in *BMI*'s regression at the 'zero' step of TSLS[6]. The variables *level of education, place of living, marital status, children, intensity of work, working industry, year of survey* are used only as controls.

Note that the gender dummy is omitted from estimation results due to the fixed effects estimation method as gender is unchanged for the studied period across all individuals.

Lewbel's procedure, modified to estimate the regression of *log_earnings* on *BMI* and controls, can be shown in three steps.

Preliminary step. Run linear regression of *BMI* on *X*, using the fixed effects method of estimation and save gained residuals *u* (robust standard errors are applied to correct for heteroskedasticity).

First step of TSLS. Obtain fitted values of *BMI* (*BMI_fitted*) by regressing *BMI* on the artificially constructed instrument and *X* with the fixed effects method and robust standard errors (SE), where the instrument is formed as a vector, which is a product of estimated residuals *u*, multiplied by centred *Z*:

$$u \times (Z - \overline{Z}). \quad (3)$$

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5 The situation, when $Z = X$, is not prohibited according to Lewbel's approach.

6 The corresponding results can be provided by the author upon request.

Second step of TSLS. Regress *log_earnings* on *BMI_fitted* and *X*, by running the fixed effects estimation with robust SE.

Two model specifications to be estimated at the last step of TSLS are used.

Model 1:

$$log\_earnings_{it} = \alpha_0 + \alpha_1 BMI_{it} + \alpha_2\, age_{it} + \alpha_3\, age_{it}^2 + \alpha_4\, education_{it} + \\ + \alpha_5\, town_{it} + \alpha_6\, reg\_ctr_{it} + \alpha_7\, married_{it} + \alpha_8\, children_{it} + \alpha_9\, log\_hours_{it} + \\ + \alpha_{10}\, exp\_p\_cap_{it} + \sum_{j=1}^{10} \beta_j \times industry\_j_{it} + \sum_{k=2014}^{2023} \gamma_k \times year\_k_t + \varepsilon_{it} + \mu_i, \quad (4)$$

where i — individual, t — year, and μ_i are individual fixed effects (on the respondent-level).

Looking at Table 3, we expect a large discrepancy in earnings of women and men subject to the industry of occupation. We also account that the attitude to overweight may depend on the industry of occupation of men and women (Flint et al., 2016; Ruggs et al., 2015; Lin, 2016; Lynch, 1996). To capture it, a model specification with the set of BMI–industry interaction dummies (Model 2) is proposed to be estimated on male and female subsamples separately.

Model 2:

$$log\_earnings_{it} = \alpha_0 + \alpha_1\, age_{it} + \alpha_2\, age_{it}^2 + \alpha_3\, education_{it} + \alpha_4\, town_{it} + \\ + \alpha_5\, reg\_ctr_{it} + \alpha_6\, married_{it} + \alpha_7\, children_{it} + \alpha_8\, log\_hours_{it} + \alpha_9 \exp\_p\_cap_{it} + \\ + \sum_{j=1}^{10} \delta_j \times industry\_j_{it} \times BMI_{it} + \sum_{j=1}^{10} \beta_j \times industry\_j_{it} + \sum_{k=2014}^{2023} \gamma_k \times year\_k_t + \varepsilon_{it} + \mu_i. \quad (5)$$

The models are estimated with the fixed effects estimation method with standard errors clustered at the individual level following Lewbel's procedure. The statistical package to be used for data analysis is Stata/MP 17.0.

5. Results

In this section, the regression analysis results from the estimation of the two models are presented. When Model 1 is estimated on a panel dataset without division into male and female subsamples, the gender dummy is omitted due to the fixed effects estimation approach because it is constant across all individuals over the whole period studied.

Based on Fig. 2, we expect some difference in the association between earnings and BMI for men and women. A Chow test is conducted to examine the hypothesis that the coefficients are equal for both female and male subsamples (the relationships in both subsamples are the same) versus the alternative that at least one coefficient differs. The F-statistics for Chow test equals 66104.45, the null hypothesis is rejected at 1% significance level meaning that the relationships in two subsamples are different. For better precision, we need to estimate our models separately on male and female subsamples. Table7 presents the estimation results of Model 1 on female subsample, male subsample, and total sample. Table 8 contains the estimation results of Model 2 on female and male subsamples.

In Table 7, we observe that the BMI coefficient estimated on a combined sample is negative and significant at 5% significance level. This coefficient can be interpreted as follows: if BMI goes up by 1 point, real earnings are expected to fall by approximately 3.2%. In other words, if we

Table 7. Estimates of the BMI effect on natural logarithm of monthly earnings (rubles, 2023 prices) with controls

Independent variable	Total sample	Women	Men
BMI	–0.032** (0.014)	–0.041* (0.024)	–0.001 (0.025)
Age	0.049*** (0.010)	0.053*** (0.015)	0.041*** (0.013)
Age-squared	–0.061*** (0.005)	–0.072*** (0.009)	–0.047*** (0.008)
Education	0.044*** (0.014)	0.049** (0.022)	0.032* (0.019)
Town	0.206** (0.089)	0.229 (0.162)	0.102 (0.073)
Regional centre	0.827*** (0.090)	0.826*** (0.163)	
Married	0.013 (0.013)	0.000 (0.016)	0.072*** (0.027)
Number of children	0.003 (0.005)	–0.008 (0.009)	0.019*** (0.007)
Intensity of work	0.212*** (0.011)	0.234*** (0.015)	0.174*** (0.016)
Year of the survey dummies	Yes	Yes	Yes
Industry of occupation dummies	Yes	Yes	Yes
Level of medical care control and constant	Yes	Yes	Yes
Observations	55648	30956	24692
Individuals	12456	6832	5624

Note. Robust standard errors are in parentheses. *** — $p < 0.01$, ** — $p < 0.05$, * — $p < 0.1$.

compare monthly earnings of normal-weight and overweight people, where the difference in BMI is around 10 points, we face about a 30% gap in real earnings. While regarding the estimation results for male and female subsamples, we can trace that only women may get earnings reduction due to being overweight with a 4.1% wage penalty following increase in BMI by 1 point. When estimating the model on male subsample, the BMI coefficient is insignificant, therefore, no evidence of either wage penalty or wage premia (as expected from Fig. 2) for overweight or obese men is found.

Results in Table 8 provide insights about how the pattern of wage variation connected with overweight may depend on the industry where a respondent works (Flint et al., 2016; Ruggs et al., 2015; Lin, 2016). The group of interaction dummies is created to capture how the working industry affects the association between BMI and earnings. As it was already mentioned, the base industry is manufacturing.

The results in Table 8 show that when we estimate the effect of BMI on earnings for separate industries on male subsample, all interaction dummies are jointly equal to zero, which again supports no earnings reduction for men due to overweight or obesity. The estimation of Model 2 on female subsample gives deeper understanding of the pattern of weight–wage penalty against women. It can be observed that interaction dummies for construction, education, trade, and consumer services and other industries are negative and significant. The largest degree of earnings penalty against

Table 8. Estimates of the BMI effect on natural logarithm of monthly earnings (rubles, 2023 prices) across industries with controls

Independent variable	Women	Men
BMI × construction	–0.091**	–0.012
	(0.046)	(0.013)
BMI × transportation & communication	–0.028	–0.011
	(0.030)	(0.013)
BMI × agriculture	0.066	–0.006
	(0.044)	(0.026)
BMI × management	–0.010	–0.068
	(0.031)	(0.043)
BMI × education	–0.030*	–0.009
	(0.018)	(0.032)
BMI × healthcare	0.065***	–0.024
	(0.022)	(0.032)
BMI × trade & consumer services	–0.049***	–0.014
	(0.017)	(0.011)
BMI × finance	0.011	–0.036
	(0.035)	(0.031)
BMI × energy industry	0.026	0.015
	(0.048)	(0.018)
BMI × other industries	–0.059***	–0.018
	(0.020)	(0.014)
Age	0.047***	0.043***
	(0.013)	(0.012)
Age-squared	–0.067***	–0.048***
	(0.007)	(0.007)
Education	0.050**	0.034*
	(0.021)	(0.018)
Town	0.260**	0.134***
	(0.109)	(0.035)
Regional centre	0.862***	
	(0.110)	
Married	–0.005	0.073***
	(0.015)	(0.027)
Number of children	–0.009	0.020***
	(0.008)	(0.007)
Intensity of work	0.234***	0.173***
	(0.014)	(0.016)
Year of the survey dummies	Yes	Yes
Industry of occupation dummies	Yes	Yes
Level of medical care control and constant	Yes	Yes
Observations	30956	24692
Individuals	6832	5624

Note. Robust standard errors are in parentheses. *** — $p < 0.01$, ** — $p < 0.05$, * — $p < 0.1$.

overweight women is found in the construction industry with about a 9% decrease in earnings following 1 point increase in BMI, compared to women with initial BMI value involved in manufacturing. If a woman works in trade and consumer services, 1 point increase in the BMI on average leads to 4.9% wage reduction ceteris paribus. The smallest penalty for extra weight is detected for women occupied in the education field — 1 point increase in the BMI is followed by around 3% earnings reduction. In such industries as transportation, agriculture, management, finance, and the energy industry, no evidence of weight–wage penalty against women is discovered. These findings correspond to the results of the previous studies, emphasizing that the presence of weight–wage penalty may depend on the type of individual's occupation (Flint et al., 2016; Ruggs et al., 2015; Lin, 2016; Lynch, 1996). On the contrary, the coefficient of healthcare industry interaction dummy is positive and significant, meaning that the earnings of overweight or obese women in healthcare are expected to be higher than that of normal-weight or under-weight female employees.

Regarding the role of other characteristics examined in explaining the variability of real earnings, it is found that monthly earnings of both men and women positively depend on their intensity of work, level of education, and the size of the place of living. These findings correspond to the results in Table 2, where higher wages for workers with higher levels of education and/or living in more urbanized areas are expected. The estimates of the intensity of work variable are significant at the 1% level and are stable numerically across the two models with higher return on extra working hours for women. The coefficient of regional centre dummy is omitted when estimation is conducted on male subsample, since no man in the sample moved to/from a regional centre over the period studied. While the coefficients of education variable, denoting premia for either vocational secondary or higher education, are unexpectedly small and significant at 5% level on female subsample and only at 1% level on male subsample. Such results may be attributed to the fact that if the variable is characterized by very little time-variation, i. e., few adult people change their level of education, while the average age of a respondent in the sample is 45 years, and its coefficient is estimated with fixed effects method, the obtained coefficient is at high risk of Type 2 error and may be low power and unreliable. This consideration is equally relevant for the place of living variables (Hill et al., 2020).

From Tables 7 and 8, it can be inferred that the coefficients of age and squared age variables are jointly significant at 1% level with a concave relationship between earnings and age. As a person gets older, his or her monthly earnings are expected to increase, but after the threshold age (around 36 years for women and 44 years for men), labour income starts to decline. In terms of the impact of marital status and the number of children on earnings, we may observe that only male earnings are affected by these factors. This result is mostly supported by the data analysis presented in Table 4. As we initially expected, married or cohabiting men on average earn more than single men with the approximate wage gap being 7%. The presence of children also has a positive significant effect on the wages of fathers, where earnings are expected to increase by around 2% with each extra child born.

Based on the estimation results and statistical analysis, it can be concluded that variables such as the BMI, age, educational level, marital status, parental status, place of living, intensity of work and occupation industry may affect the logarithm of real monthly earnings. The respondent's gender determines the presence and strength of these effects. As for the influence of the BMI on monthly earnings, an average woman in the Russian labour market is at risk of wage reduction due to being overweight. However, looking in detail, the presence and degree of wage penalty against overweight women strongly depends on the field of their occupation. No evidence of wage reduction connected with extra weight for men is observed. This means that the relationship between an individual's labour income and the BMI parameter in the Russian labour market depends on the worker's gender and only women can be penalised financially for being overweight (and obese).

6. Discussion and conclusion

This paper presents a study of how the BMI values of men and women affect their real monthly earnings based on Russian population data. Women's wages are dependent on the BMI, and female labour income tends to fall as a person gains weight. As a result, overweight women in the Russian labour market are discriminated against in terms of wages compared to normal-weight workers. The largest wage reduction due to extra weight is found for women occupied in construction, education, trade, and consumer services industries.

The data analysis for the time horizon encompassing 2013–2023 shows that real monthly earnings of women are expected to fall by around 4% if the BMI's value grows by 1 point on average. No significant association between male earnings and the BMI is found. This result confirms the observations on the negative relationship between female earnings and the BMI and no link between male wages and the BMI in Russia made by Aleksandrova and Kolosnitsyna (2018). Our results contradict the findings about a positive or concave relationship between male earnings and being overweight and no link between female earnings and being overweight which have been obtained from the analysis of RLMS–HSE data for different time periods (Kolosnitsyna, Kulikova, 2018; Kolosnitsyna, Berdnikova, 2009). One of the explanations of such striking contradiction in the results may come from bias due to the reverse causality, which is not accounted for in previous papers on Russian population data. Our findings correspond to the results of worldwide researchers on weight–wage penalty for women (Lin, 2016; Baum, Ford, 2004; Hübler, 2019; Cawley, 2004) and no association between weight and wages for men (Lin, 2016; Cawley, 2004; Averett, Korenman, 1996).

This paper contributes to the literature by providing a deeper insight into the economic consequences of being overweight in Russia at the individual level subject to gender, as this type of research has not been extensively conducted based on Russian population data. The paper takes into account a possible reverse relationship between earnings and the BMI and applies an advanced instrumental variables approach to resolve the endogeneity that occurs. During the analysis, an additional focus is paid to the role of the industry of occupation in explaining the association between earnings and the BMI. To our knowledge, this is the first research paper in Russian academic literature in this field, while there is a limited number of research papers on this topic available globally.

The limitations to this study are as follows. The set of regressors is small and does not include such exogenous variables as information on whether the individual suffers from hereditary diseases (e. g. type 1 diabetes) or the number of siblings in the family where a person grew up. The sample is restricted only to working individuals and we do not address potential bias, which may occur due to self-selection. The correction for selection bias, i. e., Heckman correction procedure, is not desirable to be applied to models estimated with fixed effect–TSLS method due to potential inconsistency of estimates (Semykina, Wooldridge, 2010). Also, there is no academic literature supporting the simultaneous application of Lewbel's and Heckman's methods. Further research should address these limitations.

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