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The impact of obesity on human capital accumulation: Exploring the driving factors

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The impact of obesity on human capital accumulation: Exploring the driving factors*

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Abstract

This study examines the impact of childhood obesity on the academic performance and human capital accumulation of high school students using data from Spain. To address potential endogeneity issues, we exploit the exogenous variation in obesity within peer groups. Specifically, we use the prevalence of obesity by gender in students' classes as an instrumental variable for individual obesity. The results indicate that obesity has a negative impact on academic achievement, particularly on general scores for girls, cognitive abilities as measured by CRT scores, financial abilities, and English grades for both boys and girls. In addition, we found a negative impact of obesity on girls' mathematics scores, while boys experienced a positive impact. We identify several key drivers of these effects, including teacher bias, psychological well-being, time preferences, and expectations related to labor market discrimination. Our analysis sheds light on the multiple influences of childhood obesity on academic outcomes and highlights the need for targeted interventions.

JEL classification: I10, I12, I15, I18, I21.

Keywords: Childhood obesity, academic performance, human capital accumulation, cognitive abilities, peer effects.

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1 Introduction

Childhood obesity and poor body weight conditions among children and adolescents have emerged as increasingly serious health concerns in developed countries (WHO, 2022). Besides, investment in human capital, primarily through education, has been recognized as one of the most important drivers of economic growth and development (Barro, 2001).

All of this has raised questions about the potential impact of obesity on academic achievement. Given the adverse effects of obesity on labor market outcomes documented by several researchers (Cawley, 2004; Morris, 2006; Morris, 2007), there is increasing interest in examining how obesity may affect the accumulation of human capital as a pathway to these labor market outcomes. Beyond the academic sphere, public policy has also begun to address this issue. In June 2023, New York City Mayor Eric Adams introduced a comprehensive plan to promote nutrition education to create healthier school communities and increase the availability of nutritious meals for students. The initiative was praised by New York State Senator Joseph P. Addabbo, Jr., who emphasized the positive effects of a balanced diet and proper nutrition on academic performance, reduced absenteeism, and improved cognitive skills. If these effects are confirmed, they could not only improve health conditions but also indirectly imrpove the academic performance of children and adolescents, thereby contributing to the overall development of human capital in terms of health and education.

This paper uses data collected from high school students in the Spanish region of Andalusia to investigate the impact of obesity on educational performance, as measured by the outcomes in various subjects and standardized tests. We examine several potential mechanisms driving the estimated effects, including teacher bias, psychological well-being, time preferences, expectations of labor market discrimination, and peer discrimination (bullying). Spain serves as a relevant case study due to the increasing prevalence of obesity in recent years and its position as one of the European countries with alarming rates of childhood obesity, nearly 13% (Sánchez-Cruz et al., 2013; Lobstein and Frelut, 2003), with overweight affecting 3 out of 10 adolescents.

Identifying the causal effect of obesity on academic performance is challenging because of potential endogeneity problems. Several factors might drive such endogeneity. First, the omission of relevant variables poses a concern; our data lacks information on family income and socio-economic background, variables that could be correlated with both obesity and academic performance. Secondly, the reliance on self-reported data for students' weight and height raises measurement error issues. There is also the issue of reverse causation, whereby poor academic performance could lead to increased body weight as a coping mechanism. Alternatively, poor academic performance could lead to psychological distress, resulting in reduced appetite and lower body weight. All these considerations require an identification strategy that addresses potential endogeneity problems to estimate the causal effect of obesity on academic performance, which is the effect of interest from a policy perspective. To address these challenges, our identification strategy exploits the exogenous variation in obesity by gender in the class in which the student is enrolled to instrument for individual obesity.

This study presents several key findings and contributions: (1) Taking advantage of the experimental information available in our data, we show that the self-reported weight and height data provided by respondents are reliable and comparable to measured data, with no evidence of intentional measurement errors. (2) Obesity has a negative impact on the academic performance of high school students. This effect is most pronounced for girls' overall scores, cognitive and financial abilities, and English grades for both genders, as well as mathematics grades for girls. (3) The negative effect estimated for girls on overall scores may be primarily due to discrimination by teachers. (4) The negative psychological well-being of obese children is also a significant factor contributing to these effects, while we do not identify bullying as a potential pathway. In addition, part of the effect of the relationship between obesity and academic achievement may be explained by differences in time preferences. (5) Although not fully conclusive, expectations of potential discrimination in the labor market may contribute to the negative impact of obesity on human capital development. This effect may be particularly pronounced in sectors such as services and digital content creation.

The remainder of the paper is organized as follows. Section 2 provides an overview of the primary literature on the subject. Section 3 presents the data and the variables used in the analysis. Section 4 describes the empirical model and the identification strategy. In Sections 5 and 6, we present the main results and explore potential mechanisms underlying our findings. Finally, Section 7 concludes.

2 Literature Review

In recent years, a growing body of research has been dedicated to exploring the impact of obesity and unfavorable body weight conditions on human capital accumulation. So far, the primary focus has been on investigating the impact of obesity on various labor market outcomes.

Empirical evidence indicates that obesity, either due to reduced labor productivity stemming from poorer health or discriminatory practices, tends to negatively affect employment and wages, particularly among females (Cawley, 2004; Morris, 2006; Morris, 2007). As a result, some researchers have begun to examine whether these adverse effects may manifest themselves earlier in individuals' economic lives, particularly in education. From a theoretical perspective, Becker (2010) proposed that rational agents, anticipating discrimination in the labor market, might adjust their human capital decisions, leading to a reduced investment of time and resources in certain academic activities.[1]

Along these lines, Sabia (2007) used instrumental variables (parents' self-reported obesity as an instrument for a child's obesity) and individual fixed effects models to examine the effects of obesity on academic performance in the United States. The results showed that obesity and a higher body mass index (BMI) were associated with lower grade point averages (GPAs). However, the association was less clear for non-white girls and boys when unobserved factors were taken into account. Ding et al. (2009) found similar effects, using genetic markers as instruments. Their results suggest significant gender differences, with female adolescents being more negatively affected by obesity than boys. Using Australian data, Black et al. (2015) found negative effects of obesity and high BMI on math and literacy scores through model estimations with fixed effects, using mother's obesity as an instrumental variable. The effects were particularly pronounced for girls, and similar in magnitude to the impact of a mother's education or smoking status during pregnancy on academic achievement. The authors argued that obesity may not be the sole driver of these results, as, after accounting for various socio-demographic factors related to the child and family, obesity and BMI did not have a significant impact.

Subsequent research by Sabia and Rees (2015) explored the psychological well-being channels that could potentially explain the effects of obesity on academic achievement, an idea initially proposed in Sabia (2007). Their results showed that psychological well-being accounted for about 30% of the observed association, particularly for females. Kaestner et al. (2011) found little evidence of a negative impact of obesity on human capital accumulation. The authors

[1] It is worth noting that while discrimination may not be the sole determinant of adverse labor market outcomes for obese workers, it appears to be the most influential factor. Studies by Baum and Ford (2004) found no evidence of negative wage effects due to additional health problems caused by obesity, but a substantial body of literature indicates strong and significant discrimination against obese workers across various economies and sectors (Rooth, 2009; Agerström and Rooth, 2011; Everett, 1990; Pagan and Davila, 1997; Bellizzi and Hasty, 1998).

raised concerns about the use of self-reported data on weight and height and potential endogeneity issues, which they were unable to address.[2] Scholder et al. (2012) challenged the view that obesity negatively affects academic performance. They were unable to find any causal effect using two genetic markers that influence obesity, suggesting that non-genetic instruments used in other studies (e.g., parent's obesity) are not valid instruments due to their potential correlation with other child and family characteristics.

Furthermore, evidence from the medical field suggests a negative association between obesity and academic achievement, although causality is often not established (Geier et al., 2007; Gortmaker et al., 1993; Gutiérrez-Fisac et al., 1996). A systematic review conducted by Hammond and Levine (2010) highlight the need for further research to explore the various mechanisms at play in this relationship. Additionally, Cohen et al. (2013) emphasized the importance of assessing causality and advocated for experimental or quasi-experimental research designs.

In the Spanish context, Gutiérrez-Fisac et al. (1996) presented empirical evidence on the relationship between obesity and education, revealing that lower levels of education were associated with higher rates of obesity in both men and women. In particular., these differences increased for women between 1987 and 1993, while they decreased for men over the same period. However, no causal evidence was provided, leaving questions about possible reverse causality or omitted variable bias. Furthermore, there has been limited exploration of the mechanisms through which the effects of obesity on human capital accumulation may manifest themselves, including discrimination, psychological well-being, or time preferences.[3] This paper contributes to filling these gaps.

3 Data

3.1 The Dataset

The data used in this study were sourced from a survey conducted as a part of the program known as *Mapeo de Competencias y Habilidades del Alumnado de Enseanza Secundaria* (COMPHAS), carried out by a team of researchers from the Loyola Behavioral Lab, a behavioral economics research institute, in collaboration with the ETEA Foundation-Development Institute

[2] It is worth noting that self-reported data on body weight and height are commonly used in the literature. Researchers such as Sabia (2007), Ding et al. (2009) and Sabia and Rees (2015) have used this type of data to construct BMI and obesity measures.

[3] The exceptions here are Sabia and Rees (2015) and, in a certain sense, Black et al. (2015).

and the Universidad Loyola Andaluca.[4]

The surveys were administered as part of an experiment carried out among students in 13 secondary schools in the Spanish region of Andalusia during the 2021-2022 academic year. It is worth noting, however, that the primary objectives of the experiment extended beyond the analysis presented in this paper. None of the experimental designs in the survey were specifically designed to collect data on body weight or obesity. Consequently, the data are treated as survey data rather than experimental data.[5]

The initial sample consisted of 4,668 individuals aged between 12 and 18, but only 2,319 of them provided information on their weight and height. After dropping individuals with missing information on the variables used in the analysis, the dataset was left with a sample of 2,025 observations.

3.2 Human Capital Variables

Several variables have been used as proxies for human capital. None of these variables relate to years of schooling or school attendance, which are commonly used as proxies for human capital. Instead, the variables used are related to academic performance or achievements, such as scores in different subjects and tests included in the survey. In principle, this should not pose any analytical problems, as Hanushek and Kimko (2000) emphasize that the quality of education, as measured by test scores, is as important, if not more important, than the quantity of education (i.e., years of schooling) in explaining economic growth and labor productivity.

First, the variable *Score* (ranging from zero to one) was constructed as a weighted average of the self-reported number of A and B grades obtained in four different subjects: mathematics, Spanish (language and reading), English, and any other subject chosen by the student. In this calculation, each A grade contributed 0.25 points, while each B grade added 0.125 points. Therefore, a score of one is given if the student has obtained four A grades. Conversely, a score of zero indicates that the student did not obtain any A or B grades during the last semester.

The second measure of human capital is the score obtained on a Cognitive Reflection Test (CRT), which students were required to complete as part of the survey. The use of this test is relatively common in the behavioral and experimental economics literature and was originally

[4] The project received ethical approval from the Ethics Committee of the Universidad Loyola Andaluca and was supported by the Spanish Ministry of Economy and Competitiveness, Excelencia-Junta, and the Agencia Andaluza de Cooperacin Internacional para el Desarrollo. The data is available at https://github.com/teenslab/datateenslab.

[5] For a full description of the recruitment process (sampling), data collection procedures, and the experiment itself see Alfonso-Costillo et al. (2022).

introduced by Frederick (2005). The test presents respondents with various questions that involve two types of answers: one that is quick, automatic, and unconscious (System 1 thinking), and another that is slower and requires more cognitive effort (System 2 thinking).[6] The higher the score on the *CRT*, the more reflective thinkers are, bringing them closer to the neoclassical rationality of the *homo economicus*. This variable is relevant not only because of its novelty in the literature on the topic of this paper and its quality,[7] but also because it serves as a strong predictor of performance on other standardized analytical tests, such as the SAT, ACT or overall GPA (Brañas-Garza et al., 2019).

The third variable is the score obtained in a test measuring *Financial abilities* (general financial mathematics). This test was also administered as part of the experiment and is arguably an accurate measure of human capital, given its strong link to future and current economic and financial decision-making.

The final category of variables used to measure human capital accumulation is the probability of obtaining an A grade in the last semester in different subjects, including mathematics, Spanish, and English. We rely on self-reported information to construct dummy variables equal to 1 if an A grade was obtained in each of these subjects, and equal to 0 otherwise.

3.3 Obesity Variables

BMI, measured as weight in kilograms divided by the square of height in meters, was constructed from self-reported weight and height measurements. A dummy for obesity was then created, taking the value one if the child's BMI exceeded a threshold specific to his/her age and sex, following the World Health Organization (WHO) criteria for childhood obesity, which is set at two standard deviations above the mean (see Onis et al., 2007). If the BMI did not exceed this threshold, the variable was assigned a value of zero.[8]

[6] In this version of the CRT, three questions were presented:

- Emilia's father has 3 daughters. The first two are called April and May. What is the name of the third? (*fast* answer: June, correct answer: Emilia).
- In a library, the number of books doubles every month. If it takes 48 months to fill the library, how long would it take to fill half of it? (*fast* answer: 24, correct answer: 47).
- If you are running a race and you pass the person in second place, where do you stand? (*fast* answer: first place, correct answer: second place).

[7] The test was administered in a classroom setting during the experiment, supervised by enumerators, making it a relatively reliable measure of students' cognitive abilities.

[8] We dropped outlier observations that fell outside the maximum BMI values set by the WHO.

3.4 Covariates

Other variables included as controls in the econometric analysis can be divided into several categories. Firstly, the sociodemographic category includes age and gender. Second, in the behavioral and psychological category, we include the frequency of fast food consumption (measured as the number of times per week), the general psychological mood (represented by a categorical variable ranging from 0 to 4), and a time preference variable constructed from the number of patient choices made by the child in a time discounting task (Multiple Price List, MPL). This task was conducted during the experiment (see Prissé, 2022 for further details). We also include a dummy variable that takes the value one if the child has experienced bullying and zero otherwise. Our definition of bullying includes both self-reports and reports from peers in the same class. The remaining category includes fixed effects for the province in which the respondent lives, as well as school and class fixed effects.

We lacked access to family background covariates, such as income or parental education, because of the children's limited knowledge of these factors. It can be argued that omitting these variables could lead to a bias in the estimated parameters. While this is a non-trivial concern, part of the problem could be mitigated by considering that the type of school (public, private, semi-private, location, and other characteristics) is highly correlated with other background variables, such as income. Therefore, it's reasonable to assume that school fixed effects partially account for these unobserved factors. In addition, the use of an instrumental variables estimation approach further addresses this issue.

3.5 Instrumental Variables

We exploit potential exogenous peer effects (Manski, 1993) and use the average obesity prevalence in each child's class by gender to instrument individual obesity in a standard Two-Stage Least Squares (2SLS) approach.[9] The identifying assumptions are that the instrument is relevant, i.e. correlated with the potentially endogenous variable, and exogenous, i.e. not correlated with the error term of the model.

The validity of the relevance criterion is well established, given the significant correlation between average class obesity and individual obesity, as shown in the reduced form specifications outlined in the following section. This correlation arises from the impact of classmates on their

[9] Morris (2006) and Morris (2007) follow a similar approach, using the prevalence of obesity in the area where the respondent lives as the instrumental variable.

peers' behaviors, including aspects such as eating habits or physical activity. It thus contributes to the network effect documented in the literature (see Trogdon et al., 2008; Halliday, Kwak, et al., 2007; Fowler and Christakis, 2008). Furthermore, this peer effect is expected to be stronger for children of the same sex, which leads us to use a gender-specific instrumental variable.

The second criterion cannot be tested statistically. Potential correlations between the instrument and the error term of the model may arise if the average class obesity by gender is correlated with unobservable specific characteristics that affect children's academic performance (Morris, 2006). However, as we include age, gender, province, school, and class fixed effects as additional covariates in the model, assuming the exogeneity of the instrument is reasonable. The inclusion of gender and school fixed effects both in the main model and in the fist-stage equation is particularly important, as our instrument is aggregated at this level. Failure to control for these variables in the model specification could lead to a correlation between the instrumental variable and the unobservables of the model, thereby compromising the validity of the instrument.

3.6 Descriptive Statistics

Table 1 presents descriptive statistics for measures of body-weight conditions, human capital accumulation, and other covariates, both for the full sample and disaggregated by obesity status. In line with previous literature, childhood obesity has a relatively high prevalence (5% of the sample).[10] Our unconditional analysis reveals that, at conventional levels of statistical significance, children classified as obese perform worse than their non-obese counterparts in all educational outcomes except mathematics. Additionally, about a quarter of the obese children in our sample are female, while almost half of the non-obese children are girls. In addition, obese children have a higher consumption of fast food and experience higher rates of bullying.

[10] Sánchez-Cruz et al. (2013) report a 13% prevalence of childhood obesity in a representative sample of Spanish children. Despite the difference with the sample average in our data, we cannot statistically reject the hypothesis that the latter differs from 13% at the 1% confidence level, indicating convergence with the population average.

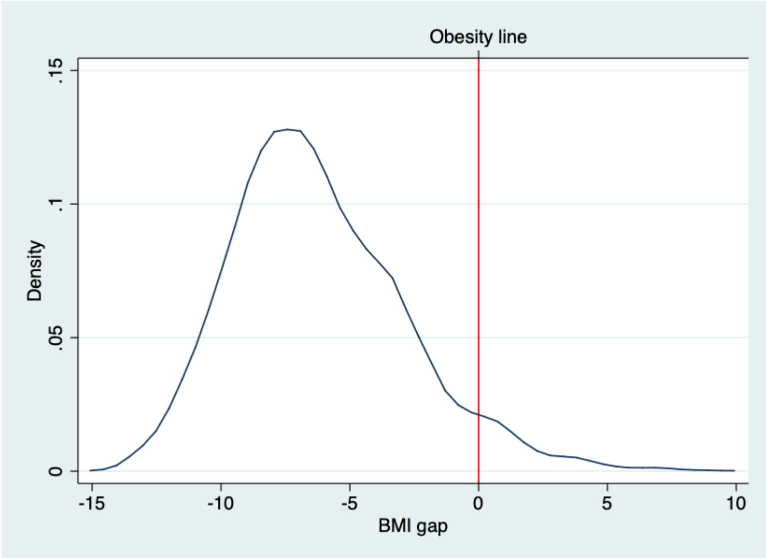
Table 1: Summary statistics

Variables	All	Obese	Non-obese	Difference in means (p-value)
BMI	20.13	27.96	19.71	0.00
	(3.31)	(2.37)	(2.79)	
Obesity	0.05	-	-	-
	(0.22)	-	-	
Score	0.26	0.22	0.27	0.05
	(0.22)	(0.18)	(0.22)	
CRT	0.53	0.46	0.53	0.00
	(0.26)	(0.25)	(0.26)	
Financial abilities	0.40	0.36	0.40	0.12
	(0.28)	(0.27)	(0.28)	
As in math	0.31	0.33	0.31	0.71
	(0.46)	(0.47)	(0.46)	
As in Spanish	0.27	0.20	0.28	0.10
	(0.45)	(0.40)	(0.45)	
As in English	0.31	0.16	0.32	0.00
	(0.46)	(0.37)	(0.47)	
Female	0.46	0.25	0.48	0.00
	(0.50)	(0.44)	(0.50)	
Age	14.01	13.89	14.01	0.39
	(1.37)	(1.42)	(1.36)	
Fast food	1.61	1.77	1.60	0.01
	(0.66)	(0.47)	(0.67)	
Psychological mood	2.90	2.62	2.92	0.00
	(0.85)	(0.99)	(0.84)	
Patience	0.55	0.57	0.55	0.71
	(0.34)	(0.36)	(0.34)	
Bullying	0.01	0.04	0.01	0.01
	(0.11)	(0.19)	(0.10)	

Notes: Standard deviations in parentheses.

Figure 1 displays the distribution of BMI within the sample. As BMI distributions typically vary according to the age and gender of children and adolescents, we present a standardized comparative measure. This measure reflects the gap between each child's actual BMI and the BMI obesity threshold for their age and gender. Similar to larger samples, the distribution appears to be normal, with a mean in line with observations in children of this age (around 20).

Figure 1: BMI gap distribution



3.7 Measurement error in Self-reported BMI

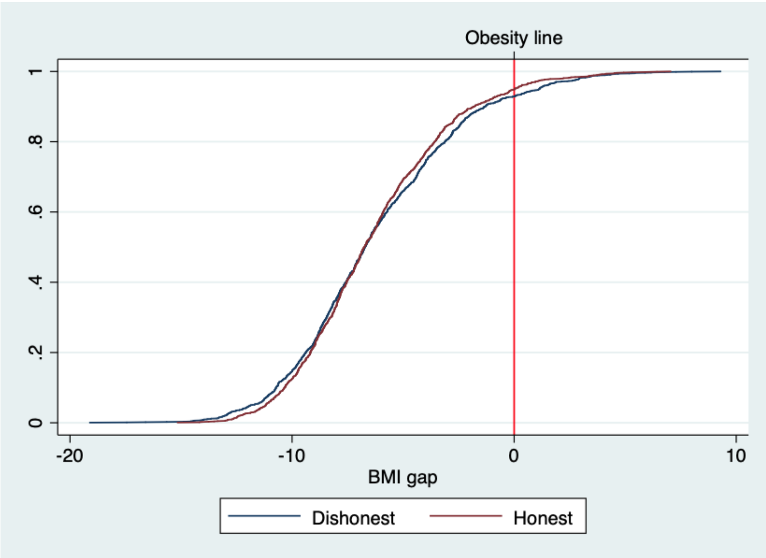
A potential concern with self-reported data on weight and height is the possibility that children might intentionally provide inaccurate responses, to report a lower (or higher, depending on their body condition or self-perception) BMI than their actual values. If this is the case, we expect to observe differences in BMI between children who report honestly and those who report dishonestly across the entire distribution. This could systematically shift the distribution either to the left, to the right, or toward the mean, thereby exacerbating measurement error bias in the analysis.

In Figure 2, we investigate whether the distribution of BMI reported by honest children is similar to that of those dishonest children using Kolmogorov-Smirnov tests for equality of distributions. Failure to reject the hypothesis that the two distributions are equal would provide additional evidence that, despite unintentional measurement error, self-reported weight and height data can reasonably be used as a proxy for children's true weight and height.

The variable $Honesty$ was measured by a task in which children were randomly assigned a colored number to memorize. Each colored number was associated with a hypothetical payoff. They were then instructed to identify the color of the number they received, with the associated payoffs displayed in parentheses next to the response options. There were no restrictions preventing participants from claiming a different colored number with a higher associated payoff than the one they were initially randomly assigned. Both the number assigned and the answer given by each child were recorded. A dummy variable for honesty was then created, taking the value of one if the child gave an honest answer and zero otherwise.

In this context, dishonesty is considered a white lie, implying no harm or disadvantage to others, similar to intentionally misreporting one's height or weight. The expectation is that individuals who were dishonest in the described task would be more likely to be dishonest in reporting their weight and height than those who were honest in the task. We find that the BMI distributions of honest and dishonest children are statistically identical (the p-value of the test is $p = 0.52$). This finding supports the validity of using self-reported measures of weight and height in the analysis, suggesting the absence of intentional measurement error.

Figure 2: Cumulative distributions of BMI gap by honesty



Notes: Kolmogorov-Smirnov test for equality of distributions ($p = 0.52$).

Another concern with the use of a self-reported measure of BMI is the possibility that obese children may choose not to report weight or height data due to feelings of shame or fear of stigma, potentially introducing selection bias.[11] This issue has been either ignored in the literature or addressed by arguing that missing responses are randomly distributed or attributed to observable characteristics. However, Dutz et al. (2021) find that selection into responding may introduce a substantial bias. The direction in which this bias might alter the estimates is of interest, and Table 2 presents the average differences in academic outcomes between respondents who provided weight and height data and those who chose not to. The table indicates that, on average, non-respondents have poorer academic outcomes on most human capital measures, except for *Score*, where both groups are similar at conventional statistical levels. Taking this

[11] Children were given the option to decide whether to report this information during the survey.

into account, and assuming that a majority of obese children may be in the non-respondent group, it follows that the effects of interest, if any, are likely to be underestimated in the presence of a potential selection bias.

Table 2: Human capital proxies for BMI respondents and non-respondents

Variables	Respondents	Non-respondents	Difference in means (p-value)
Score	0.26	0.26	0.98
	(0.21)	(0.21)	
CRT	0.52	0.47	0.00
	(0.27)	(0.27)	
Financial abilities	0.39	0.32	0.00
	(0.28)	(0.28)	
As in math	0.30	0.21	0.00
	(0.46)	(0.41)	
As in Spanish	0.26	0.18	0.00
	(0.44)	(0.38)	
As in English	0.28	0.26	0.41
	(0.45)	(0.43)	

Notes: Standard deviations in parentheses.

4 Empirical Model

Our starting point for examining the impact of obesity on human capital accumulation using cross-sectional data is based on the following linear equation:

$$h_i = \beta_0 + \beta_1 Obese_i + \beta_2 Obese_i \times Female_i + \beta_3 Female_i + \beta_4' X_i + \theta_p + \delta_s + \zeta_c + \epsilon_i, \qquad (1)$$

where h_i denotes one of the different human capital measures for child i. The variable $Obese_i$ is a dummy that takes value 1 if the child is obese and 0 otherwise. Similarly, $Female_i$ is another dummy taking the value 1 if the child is female and 0 otherwise. The vector X_i contains socio-demographic, behavioral, and psychological control variables. In addition, θ_p, δ_s, and ζ_c represent province, school, and class fixed effects respectively. The term ϵ_i is the error term of the model.[12]

The coefficients of interest are β_1 and β_2. β_1 reflects the average impact of obesity on academic achievement, while β_2 captures the differential effect of obesity for girls compared to boys. We first estimate the model using Ordinary Least Squares (OLS). For these estimates to

[12] Although the relationship of interest for binary human capital measures, such as obtaining an A grade in different subjects, is inherently non-linear, for simplicity we specify it using linear probability models (LPM).

be consistent, the error term of the model should not be correlated with the main variable of interest, $Obese_i$. However, as obesity is likely to be endogenous to the process of human capital accumulation, OLS estimates from Equation 1 would fail to capture the causal effect of obesity on academic outcomes. Several factors point to the endogeneity of obesity:

First, as discussed above, the lack of data on family income or socioeconomic background could lead to omitted variable bias, as there may be unobserved factors that are correlated with both obesity and academic performance. Although school fixed effects may partially address this problem, it may persist. Second, self-reported weight and height introduce the possibility of measurement error. Although the distribution of BMI appears normal and there's no statistical evidence of systematic differences in reporting between honest and dishonest children, it's still uncertain whether children accurately reported their true weight and height. Finally, there is the possibility of reverse causation, where low academic achievement leads to increased body weight or vice versa.

Given the cross-sectional nature of the data and concerns about endogeneity, an instrumental variables (IV) estimation strategy is employed to address these issues. Specifically, Equation 1 is estimated using 2SLS, where individual obesity ($Obese_i$) is instrumented with the gender-specific average obesity prevalence in the class in which child i is enrolled, denoted as $\overline{Obese}_{cg}$. The 2SLS estimates can be interpreted as the Local Average Treatment Effects (LATE), or the effect on compilers, i.e., the effect for those individuals whose behavior changes in response to variations in the instrument (Imbens and Angrist, 1994).

5 Estimation Results

5.1 OLS Estimates

The main regression results from the OLS estimates are presented in Tables 3 and 4. These tables report both the coefficients for the average impact of the dummy for obesity ($Obese$) on educational outcomes, as well as the differential effect for girls ($Female \times Obese$). It also highlights the impact of $Female$. The full sets of estimation results are presented in the Appendix. We want to emphasize the importance of accounting for class fixed effects when interpreting our results. Therefore, we present the results for both models: one without class fixed effects and one with class fixed effects included in the model specification. The adjustment of standard errors is crucial to address the potential lack of independence between observations. Following Morris (2006), we account for within-group correlation and clustering within primary sampling units by using Huber/White/sandwich robust variance estimators in our analysis.

Table 3: OLS estimates for general scores, cognitive, and financial abilities

VARIABLES	(1) Score	(2) Score	(3) CRT	(4) CRT	(5) Financial abilities	(6) Financial abilities
Obese	-0.008	-0.008	-0.065**	-0.057*	-0.027	-0.011
	(0.022)	(0.023)	(0.029)	(0.030)	(0.031)	(0.029)
Female × Obese	-0.069**	-0.040	-0.062	0.008	-0.097*	-0.040
	(0.034)	(0.037)	(0.060)	(0.062)	(0.053)	(0.053)
Female	0.044***	0.046***	-0.029**	-0.026**	-0.086***	-0.091***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.013)
Constant	0.368***	0.769***	0.196**	1.080***	-0.312***	0.916***
	(0.066)	(0.115)	(0.088)	(0.206)	(0.087)	(0.203)
Observations	2,025	2,025	2,025	2,025	2,025	2,025
R-squared	0.068	0.140	0.042	0.152	0.092	0.200
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering. Controls include age, weekly fast food consumption, psychological mood, time preferences (number of patient choices), and bullying.

The results in Table 3 suggest that there is no statistically significant effect of obesity on the overall score for boys (Column (1)). However, a negative impact is estimated for girls, corresponding to a reduction of 0.35 standard deviations (SD). Notably, this effect loses significance when class fixed effects are taken into account (Column (2)). Regarding CRT scores, both obese boys and girls show lower cognitive ability, scoring 0.65 points lower out of 10 compared to their non-obese peers. No significant differential effect was found for girls. This reduction corresponds to a decrease of 0.22 SD. Importantly, this negative impact remains statistically significant even after controlling for class fixed effects, and the magnitude slightly decease to 0.57 points. When examining financial abilities, there is no evidence of a significant impact of obesity for boys, regardless of whether class fixed effects are taken into account. For girls, there is evidence of a negative effect without class-fixed, but it is only marginally significant. This negative effect disappears when class-fixed effects are included in the model.

Table 4: OLS estimates for obtaining an A grade in different subjects

VARIABLES	(1) Mathematics	(2) Mathematics	(3) Spanish	(4) Spanish	(5) English	(6) English
Obese	0.099*	0.126**	-0.009	0.004	-0.113***	-0.097**
	(0.053)	(0.053)	(0.043)	(0.045)	(0.041)	(0.042)
Female × Obese	-0.247***	-0.262***	0.003	0.036	0.031	0.041
	(0.082)	(0.080)	(0.098)	(0.100)	(0.096)	(0.099)
Female	-0.010	-0.006	0.107***	0.106***	0.092***	0.085***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)
Constant	0.968***	1.612***	0.624***	1.616***	0.665***	1.835***
	(0.140)	(0.278)	(0.135)	(0.275)	(0.137)	(0.259)
Observations	2,025	2,025	2,025	2,025	2,025	2,025
R-squared	0.112	0.189	0.112	0.193	0.113	0.209
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering. Controls include age, weekly fast food consumption, psychological mood, time preferences (number of patient choices), and bullying.

In the analysis of achieving A grades in different subjects (Table 4), the OLS estimates from the Linear Probability Model show a positive impact of obesity on the attainment of an A grade in mathematics for boys (Columns (1) and (2)). This result, in line with Sabia (2007), could be due to psychological stress caused by poor academic performance, leading to reduced appetite and subsequent weight loss. Alternatively, it could be that the learning curve of this subject is such that it becomes more costly to invest in improving the weight condition of obese boys compared to other subjects. Conversely, this relationship is negative for girls, with obese girls on average being 13.6 percentage points (pp.) less likely to achieve an A grade in mathematics in the model that includes class fixed effects. Notably, the likelihood of obtaining an A grade in Spanish Language and Literature does not seem to be related to obesity (Columns (3) and (4)). On the other hand, for both boys and girls, obesity is associated with a lower probability of obtaining an A grade in English (about 10 pp. less than their non-obese counterparts). For all the subjects considered in Table 4, there are no significant differences in the estimated effects when class fixed effects are included in the model. The heterogeneity of the results across subjects is further explored in the *Mechanisms* subsection.

5.2 IV Estimates

Tables 5 and 6 present 2SLS estimates for the different measures of human capital. In these estimates, we use the average obesity prevalence within each child's class by gender as the instrument. It's crucial to emphasize that this instrument remains highly relevant even when the province, school, and, importantly, class fixed effects are included in the model specification (see First stage estimates in Panel B in Tables 5 and 6). Given that our instrument is aggregated at the class (and gender) level, it is essential to include class fixed effects in both the main and reduced-form models for the potentially endogenous variables. This step helps to establish the genuine presence of exogenous obesity peer effects while mitigating the risk of attributing them to unobservable class characteristics. Additionally, we present the results of the Hausman test, which assesses the null hypothesis of the exogeneity of obesity.

Table 5: 2SLS estimates for general scores, cognitive, and financial abilities

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Score	Score	CRT	CRT	Financial abilities	Financial abilities
Panel A: Two Stage Least Squares						
Obese	-0.035	-0.017	-0.141	-0.076	-0.287***	-0.223**
	(0.061)	(0.088)	(0.086)	(0.112)	(0.090)	(0.105)
Female × Obese	-0.209	-0.142	-0.436**	-0.149	-0.219	0.007
	(0.143)	(0.191)	(0.197)	(0.244)	(0.174)	(0.224)
Female	0.046***	0.049***	-0.022	-0.022	-0.096***	-0.102***
	(0.011)	(0.013)	(0.014)	(0.015)	(0.014)	(0.016)
Constant	0.355***	0.892***	0.165**	1.052***	-0.186**	1.029***
	(0.060)	(0.143)	(0.083)	(0.234)	(0.081)	(0.233)
Observations	2,025	2,025	2,025	2,025	2,025	2,025
R-squared	0.060	0.137	0.003	0.146	0.032	0.176
Hausman F-statistic	1.009	0.219	5.312***	0.402	10.583***	2.707*
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	No	Yes	No	Yes	No	Yes
Panel B: First stage for Obese and Female × Obese						
Class obesity	1.011***	1.005***	1.011***	1.005***	1.011***	1.005***
	(0.104)	(0.100)	(0.104)	(0.100)	(0.104)	(0.100)
Female × Class obs.	1.009***	1.008***	1.009***	1.008***	1.009***	1.008***
	(0.203)	(0.227)	(0.203)	(0.227)	(0.203)	(0.227)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering. Controls include age, weekly fast food consumption, psychological mood, time preferences (number of patient choices), and bullying. Class obesity in Panel B refers to gender-specific obesity prevalence. Models in Panel B includes all controls

Columns (1) and (2) of Table 5 show no significant evidence of an effect of obesity on general scores, for both boys and girls. However, according to the Hausman test, we cannot reject the hypothesis that the OLS estimates are consistent. We therefore consider the OLS results from Table 3 as our preferred estimates. For the CRT scores, the Hausman test similarly fails to reject the null hypothesis that obesity is exogenous. If anything, obesity may affect cognitive abilities equally for boys and girls, as the OLS estimates suggest.

When examining financial abilities, the 2SLS estimation results starkly differ from those obtained by OLS. We find a statistically significant negative effect of obesity, with no differential impact for girls. It is important to note that there are no differences in the estimation results when class fixed-effects are included in the model specification. Moreover, the Hausman test indicates the endogeneity of obesity, even when class fixed effects are included, at the 10% confidence level. Therefore, evidence suggests that the OLS estimates are inconsistent for this particular outcome, and the IV estimates should be used to interpret our results.

Table 6: 2SLS estimates for obtaining an A grade in different subjects

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Mathematics	Mathematics	Spanish	Spanish	English	English
			Panel A: Two Stage Least Squares			
Obese	0.023	0.268	-0.035	0.019	-0.115	0.098
	(0.142)	(0.194)	(0.126)	(0.161)	(0.126)	(0.181)
Female × Obese	-0.013	-0.230	0.161	0.502	0.076	-0.147
	(0.278)	(0.370)	(0.281)	(0.389)	(0.270)	(0.366)
Female	-0.020	-0.000	0.101***	0.094***	0.091***	0.100***
	(0.023)	(0.026)	(0.022)	(0.025)	(0.023)	(0.026)
Constant	0.814***	1.552***	0.427***	1.813***	0.721***	2.033***
	(0.131)	(0.297)	(0.121)	(0.312)	(0.125)	(0.277)
Observations	2,025	2,025	2,025	2,025	2,025	2,025
Hausman F-statistic	0.400	0.493	0.182	1.227	0.018	0.592
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	No	Yes	No	Yes	No	Yes
			Panel B: First stage for Obese and Female × Obese			
Class obesity	1.011***	1.005***	1.011***	1.005***	1.011***	1.005***
	(0.104)	(0.100)	(0.104)	(0.100)	(0.104)	(0.100)
Female × Class obs.	1.009***	1.008***	1.009***	1.008***	1.009***	1.008***
	(0.203)	(0.227)	(0.203)	(0.227)	(0.203)	(0.227)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering. Controls include age, weekly fast food consumption, psychological mood, time preferences (number of patient choices), and bullying. Class obesity in Panel B refers to gender-specific obesity prevalence. Models in Panel B includes all controls

Table 6 presents IV results for achieving A grades in different subjects. In all cases, the

Hausman tests do not reject the exogeneity of obesity. Therefore, our preferred estimates are the ordinary least squares (OLS) results presented above.

The evidence presented aligns with existing literature, indicating a negative impact of obesity on academic achievement. This effect is particularly pronounced in the case of general scores for girls, as well as in CRT and financial abilities, and the probability of obtaining an A grade in English for both boys and girls. Interestingly, girls show a negative impact on the probability of achieving an A grade in mathematics, while boys show a positive impact. The following section explores potential mechanisms that might explain these relationships and effects.

6 Potential Mechanisms

This section explores potential mechanisms that might explain our findings. Taking advantage of a rich set of available variables in our data, we can examine potential channels often theorized as pathways through which obesity might impact human capital accumulation. Specifically, we examine evidence regarding teacher discrimination, psychological well-being, bullying (peer discrimination), time preferences, and expectations related to labor market discrimination as potential drivers.

Following a similar strategy to Sabia and Rees (2015), Table 7 presents the percentage change in the estimated coefficients measuring the impact of obesity on academic achievement when controlling for each of the potential drivers.[13] Two models were estimated: one excluding each variable (class fixed effects, psychological mood, bullying, and time preferences) and another including them as controls. The models were estimated using the most appropriate method according to the Hausman test previously performed, i.e., OLS for general scores, CRT, and obtaining A grades in maths and English; and 2SLS for financial abilities. We then calculated the percentage differences in the obesity coefficient and in the coefficient that captures the differential effect for girls in the latter specification compared to the former. This measure reflects the relative magnitude of the omitted variable bias and provides evidence of the potential mediation of different variables in the relationship between obesity and human capital accumulation (Heckman and Pinto, 2015).

[13]Note that obtaining an A grade in Spanish is not included in the table as no significant effect was found for this variable.

Table 7: Percentage change in obesity coefficients upon addition of each "mechanism" variable

	All controls		*Excluding Class FE*		*Excluding Psy. Mood*		*Excluding Bullying*		*Excluding Patience* height	
OUTCOMES	Obese	Female × Obese	Obese	Female × Obese	Obese	Female × Obese	Obese	Female × Obese	Obese	Female × Obese
Score	-0.008	-0.040	-0.009	-0.069**	-0.019	-0.035	-0.008	-0.041	-0.006	-0.041
% change			-11.1%	-42.0%	-57.9%	14.3%	0%	-2.4%	33.3%	-2.4%
CRT	-0.057*	0.008	-0.065**	-0.062	-0.063**	0.010	-0.057*	0.008	-0.054*	0.005
% change			-12.3%	-112.9%	-9.5%	-20.0%	0%	0%	5.5%	60.0%
Fin. abilities	-0.223**	0.007	-0.287***	-0.219	-0.231**	-0.017	-0.223**	-0.012	-0.211**	-0.013
% change			-22.3%	-94.1%	-3.5%	-23.5%	0%	8.3%	5.7%	0%
Prob. A Maths	0.126**	-0.262***	0.099*	-0.247***	0.089	-0.246***	0.124**	-0.259***	0.128**	-0.263***
% change			27.3%	6.1%	41.6%	6.5%	1.6%	1.1%	-1.6%	-0.4%
Prob. A English	-0.097**	0.041	-0.113***	0.031	-0.127***	0.054	-0.096**	0.040	-0.095**	0.040
% change			-14.1%	32.2%	-23.6%	-24.1%	1.0%	2.5%	2.1%	2.5%

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering. All controls include age, weekly fast food consumption, psychological mood, time preferences (number of patient choices), bullying, province, schools, and class fixed effects. Financial abilities estimates are obtained from 2SLS, and the estimates for the remaining outcomes are obtained from OLS.

The first two columns present the coefficients for the variables $Obese$ and $Female \times Obese$ obtained when including all control variables (see Tables 3, 4, and 5). The next two columns show the effects when class fixed effects are excluded from the model specification. The effect of $Obese$ for boys remains non-significant before and after the inclusion of class fixed effects. Notably, the significant impact of obesity on girls' general score disappears when class fixed effects are included. In particular, the interaction between obesity and gender not only reduces the magnitude of the differential effect observed in girls by 42% but also eliminates its statistical significance.

Although we lack explicit information to control for teacher fixed effects, we argue that at least some of the significant and stronger effects found when omitting class fixed effects could stem from teacher discrimination.[14] The reason is that, for all other outcomes, including class fixed effects either do not alter the lack of significance of the estimated coefficients or account for a smaller percentage of the relationship (e.g., 12.3% and 22.3% decreases in the effects on CRT and financial abilities, respectively). However, we would expect the teacher discrimination mechanism to be particularly relevant in the case of general scores, as they are collected and assessed by teachers. In contrast, CRT scores and financial abilities are not obtained from a teacher evaluation but through tests conducted during the experiment. This makes them less susceptible to teacher bias, which is compatible with our results that the interaction term in the

[14] Note that this interpretation would be exact if each teacher taught exclusively in one class, which was not necessarily the case in all schools within our dataset. Notice that Sabia, 2007 only consider the quality of the relationship between the child and the teacher in their analysis

general scores specification is the only estimate to lose all statistical significance when controlling for class fixed effects. This lends credibility to the hypothesis of teacher discrimination against obese girls.

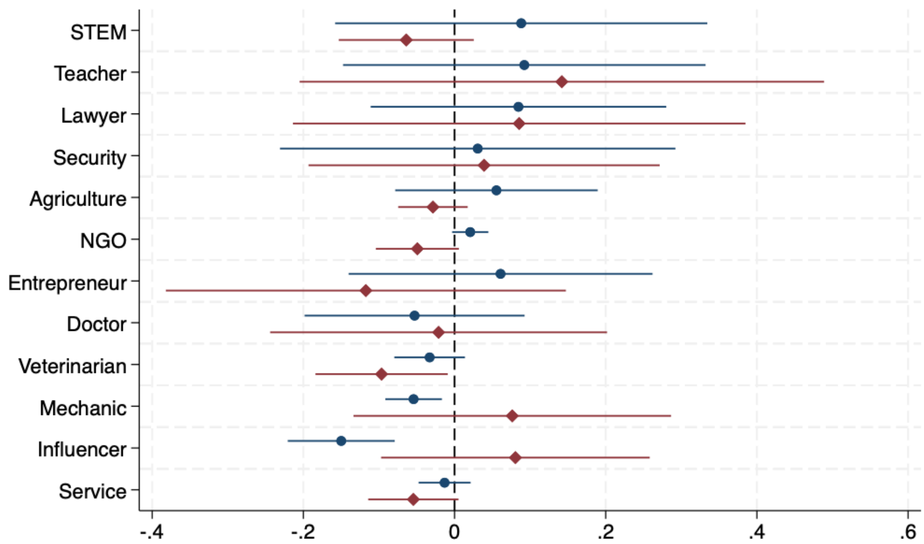
Table 5 also shows that including a proxy for mental health in the regression does not alter the lack of statistically significant effect but tends to reduce the negative effect of obesity on academic performance, except for the probability of obtaining an A grade in mathematics for girls. This is in line with previous studies by Sabia and Rees (2015) and Cawley (2004), with the latter reporting similar results regarding the effects of obesity on wages. For CRT, the statistically significant coefficients decreased by 9.5% (from -0.063 to -0.057). Given the positive impact of psychological mood on academic outcomes (see Tables in the Appendix), these results suggest a negative conditional correlation between obesity and psychological well-being: on average, obese students tend to have poorer mental health, likely influenced by their body self-perception. This perception could potentially impact their motivation and awareness of these academic activities. The increase in the positive effect for boys achieving an A grade in mathematics (from 0.089 to 0.126) further supports this interpretation.

Table 7 indicates that, overall, the impact of the bullying channel on the relationship between obesity and human capital is not significant (see Columns (7) and (8)). Similar to mental health, one might expect that including the bullying variable would reduce the magnitude of the coefficients. However, the impact of this variable on the outcomes is not statistically significant (see Tables in the Appendix), suggesting that bullying or class (peer) discrimination may not be a relevant mechanism in explaining the effect of obesity on education.

Time preferences and subjective discount rates are potentially important factors influencing the adverse effects of obesity on educational outcomes. In this regard, the last two columns of Table 7 show that the negative impact of obesity on CRT, financial abilities, and the probability of getting an A in English, is slightly increased when this mechanism is accounted for in the model specification (note that the coefficients are not statistically significant for general scores in any case). Given that patience is positively associated with better academic performance (see Tables A1 through A6 in the Appendix), this result is consistent with a positive conditional correlation between obesity and patience. The mechanism could work as follows: when individuals face the choice between improving their physical well-being and improving their academic performance (both patience-intensive tasks), those who stand to benefit more from academic pursuits may allocate more time and effort to academics at the expense of maintaining their weight (Sabia, 2007). In other words, there is a trade-off between devoting time to improving academic performance and reducing obesity (e.g., through exercise or healthier dietary choices). This mechanism may also explain the slight reduction in the positive coefficient of obesity on the probability of getting an A grade in mathematics for boys.

Finally, we explore the extent to which expectations regarding labor market discrimination drive the findings presented in this paper. According to theory, individuals who anticipate discrimination in the labor market may adjust their decisions regarding human capital investments, leading to a reduced commitment to certain academic activities in terms of time and resources (Becker, 2010; Becker, 2009). We estimate Linear Probability Models to analyze the association between obesity and the probability of willingness to work in different sectors for boys and girls.[15] If, on average, obese children are less likely to will to work in sectors where discrimination is prevalent, it follows that they may allocate fewer resources and less time to certain human capital investments, guided by their (likely imperfect) information about the labor market. Figure 3 displays these linear regressions' estimated coefficients and confidence intervals.

Figure 3: Associations between obesity and preferences for different jobs



Notes: Blue dotted estimates are for boys, and red diamond-shaped estimates are for girls. All coefficients are obtained by regressing each type of job on obesity, its interaction with gender, all the controls specified above, and province, school, and class fixed effects.

Most of the coefficients in Figure 3 are not statistically significant, suggesting that there is limited conclusive evidence in our data regarding expectations about labor market discrimina-

[15] Questions about the willingness to work in different sectors are also included in the survey.

tion as a potential mechanism. This would be partly attributed to a power issue, as this analysis reduces the sample size to 518 observations. Nevertheless, some notable cases provide valuable insights. For example, obese girls have a 5 pp. lower probability of expressing a willingness to work in the services sector (at the 10% confidence level), a 10 pp. lower probability of aspiring to become a veterinarian, and a 5 pp. lower probability of interest in working for an NGO (also at the 10% confidence level). Furthermore, obese boys are 5 pp. less likely than their non-obese counterparts to work as mechanics. They are also 16 pp. less likely to aspire to become YouTubers, influencers, or social media content creators. Interestingly, existing literature suggests that positions requiring face-to-face or more direct customer interaction often experience higher levels of discrimination, particularly in the case of women (Bellizzi and Hasty, 1998; Everett, 1990; Harper, 2000). This finding may explain why obese girls appear less interested in the service sector or why obese boys are less likely to pursue roles as online content creators, as these positions involve greater public exposure. In addition, Baum and Ford (2004) found evidence of potential employer discrimination against obese workers in the craft sector in the US, which is consistent with the hypothesis that obese boys may be less inclined to work as mechanics due to expected labor market discrimination. However, the latter argument is controversial, with some attributing it to statistical discrimination or productivity effects.

If obese children are less willing to work in certain sectors due to potential labor market discrimination, this could serve as a non-trivial mechanism contributing to the negative impact of obesity on human capital accumulation. In response, children may act rationally by allocating fewer resources and less attention to acquiring certain relevant knowledge which is more valued in sectors where discriminatory market failures occur. Consequently, this could lead to a decrease in their academic achievement.

7 Conclusions

This study examines the impact of obesity on human capital accumulation and explores the potential mechanisms driving these effects. Specifically, it analyzes the role of teacher discrimination, psychological well-being, bullying (peer discrimination), time preferences, and expectations regarding labor market discrimination as factors driving the estimated impacts. Using cross-sectional data obtained from an experiment conducted in secondary schools across different localities in Andalusia (Spain), we exploit the exogenous variation stemming from in-class obesity peer effects by gender to account for potential endogeneity problems. We provide evidence suggesting that our self-reported data on weight and height are unlikely to be affected by intentional or systematic measurement errors from respondents. Therefore, the self-reported data we use are considered as valid as measured data, although unintentional measurement errors cannot be entirely ruled out.

The main findings of this paper can be summarized as follows: (1) Obesity is associated with diminished academic performance in several educational outcomes, in particular in general scores for girls, cognitive abilities as measured by CRT scores, financial abilities, and English grades for both boys and girls. It also has a negative effect on the probability of achieving an A grade in mathematics for girls, but a positive effect for obese boys. This latter result indicates that the time devoted to achieving academic success and the time required to improve their weight condition appear to be substitutes for obese boys. (2) Class-fixed effects emerge as a significant driver of the negative impact of obesity on general scores for girls, as controlling for these effects eliminates the negative impact. Given that the teachers record general scores, and that class-fixed effects either do not significantly affect other educational outcomes recorded during the experiment or account for a smaller proportion of the effect, we conclude that teacher discrimination may be a crucial driver of the negative impact of obesity on girls' general scores. (3) The psychological well-being of obese children may account for up to 23% of the estimated negative effect on the probability of getting an A grade in English and up to 9.5% of CRT. However, there is no evidence indicating that bullying explains this relationship. (4) Time preference also explains part of this relationship (i.e. 5.5% and 6.2% for CRT and financial abilities, respectively), with time spent on improving academic performance potentially acting as a substitute for time spent on reducing obesity. (5) Although not fully conclusive, expectations of potential labor market discrimination may play a role in the negative impact of obesity on human capital development. These effects may be particularly noticeable in the service sector and the creation of internet content.

These findings have relevant policy implications. First, although it may seem obvious, policies aimed at reducing the prevalence of obesity are likely to be the most effective and feasible approaches to mitigating the adverse effects of poor body weight conditions on educational outcomes. Policies to reduce obesity have a direct positive impact on human capital by improving health and an indirect positive impact by improving academic performance. In addition, particular attention should be paid to girls, who appear to be more affected. This focus could potentially improve their future economic opportunities in the labor market. For example, mitigating the negative effects observed in obese girls' mathematics performance could enable them to pursue higher education studies that require mathematical skills, which are often associated with better-paid careers (e.g., STEM fields), thus promoting equal opportunities.

Understanding the mechanisms underlying these effects is crucial for policymakers. Our analysis suggests that implementing awareness-raising programs for teachers, anonymizing exams, projects, or homework to minimize potential discrimination against obese girls, and providing mental health support for obese children could serve as effective policy complements. It is also important to recognize the relationship between the time investments required for academic performance and the time required to reduce obesity. Policies should aim to reduce the opportunity costs of improving children's body weight conditions, for example by facilitating access to physical activity or healthy eating.

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Appendix

Table A1: OLS estimates for score

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Obese	-0.023	-0.011	-0.008	-0.008	-0.008
	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)
Female × Obese	-0.063*	-0.065*	-0.067**	-0.069**	-0.040
	(0.033)	(0.034)	(0.034)	(0.034)	(0.037)
Age	-0.022***	-0.018***	-0.019***	-0.019***	-0.057***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
Female	0.043***	0.043***	0.044***	0.044***	0.046***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Fast food	0.034***	0.030***	0.028***	0.026***	0.021**
	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Mood general		0.037***	0.037***	0.037***	0.033***
		(0.006)	(0.006)	(0.006)	(0.006)
Standardized Patience		0.040***	0.037***	0.037***	0.030**
		(0.014)	(0.014)	(0.014)	(0.015)
Bullying		-0.001	-0.005	-0.004	0.008
		(0.041)	(0.040)	(0.041)	(0.044)
Constant	0.527***	0.343***	0.377***	0.368***	0.769***
	(0.051)	(0.055)	(0.059)	(0.066)	(0.115)
Observations	2,025	2,025	2,025	2,025	2,025
R-squared	0.039	0.063	0.066	0.068	0.140
Province FE	No	No	Yes	Yes	Yes
School FE	No	No	No	Yes	Yes
Class FE	No	No	No	No	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering.

Table A2: OLS estimates for CRT

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Obese	-0.069**	-0.064**	-0.061**	-0.065**	-0.057*
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)
Female × Obese	-0.062	-0.060	-0.061	-0.062	0.008
	(0.060)	(0.060)	(0.060)	(0.060)	(0.062)
Age	0.018***	0.020***	0.019***	0.018***	-0.049***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.014)
Female	-0.030**	-0.032***	-0.031**	-0.029**	-0.026**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Fast food	0.016	0.012	0.014	0.013	0.007
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Mood general		0.020***	0.021***	0.021***	0.018**
		(0.007)	(0.007)	(0.007)	(0.007)
Standardized Patience		0.077***	0.075***	0.075***	0.058***
		(0.017)	(0.017)	(0.017)	(0.017)
Bullying		-0.016	-0.019	-0.010	-0.008
		(0.052)	(0.052)	(0.055)	(0.062)
Constant	0.287***	0.158**	0.186**	0.196**	1.080***
	(0.064)	(0.074)	(0.082)	(0.088)	(0.206)
Observations	2,025	2,025	2,025	2,025	2,025
R-squared	0.018	0.033	0.034	0.042	0.152
R-squared	0.039	0.063	0.066	0.068	0.140
Province FE	No	No	Yes	Yes	Yes
School FE	No	No	No	Yes	Yes
Class FE	No	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering.

Table A3: IV estimates for financial abilities

	(1)	(2)	(3)	(4)	(5)	
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	
Panel A: Two Stage Least Squares						
Obese	-0.223**	-0.219***	-0.254***	-0.287***	-0.223**	
	(0.087)	(0.085)	(0.088)	(0.090)	(0.105)	
Female × Obese	-0.322*	-0.313*	-0.238	-0.219	0.007	
	(0.177)	(0.173)	(0.171)	(0.174)	(0.224)	
Age	0.034***	0.037***	0.039***	0.036***	-0.049***	
	(0.005)	(0.005)	(0.005)	(0.005)	(0.014)	
Female	-0.090***	-0.092***	-0.094***	-0.096***	-0.102***	
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	
Fast food	0.026*	0.022	0.024*	0.021	0.006	
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	
Mood general		0.026***	0.024***	0.024***	0.024***	
		(0.007)	(0.008)	(0.008)	(0.007)	
Standardized Patience		0.058***	0.056***	0.058***	0.048***	
		(0.018)	(0.018)	(0.018)	(0.017)	
Bullying		0.024	0.028	0.033	0.032	
		(0.053)	(0.055)	(0.055)	(0.054)	
Constant	-0.043	-0.190**	-0.230***	-0.186**	1.029***	
	(0.069)	(0.075)	(0.076)	(0.081)	(0.233)	
Observations	2,025	2,025	2,025	2,025	2,025	
R-squared	0.017	0.032	0.035	0.032	0.176	
Province FE	No	No	Yes	Yes	Yes	
School FE	No	No	No	Yes	Yes	
Class FE	No	No	No	No	Yes	
Panel B: First stage for Obesity						
Class obesity	1.025***	1.019***	1.012***	1.011***	1.005***	
	(0.105)	(0.104)	(0.104)	(0.104)	(0.100)	
Female × Class obs.	-0.011	-0.020	-0.011	-0.014	-0.010	
	(0.218)	(0.225)	(0.227)	(0.226)	(0.229)	(0.262)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering.

Table A4: OLS estimates for As in mathematics

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Obese	0.054	0.093*	0.102*	0.099*	0.126**
	(0.055)	(0.053)	(0.052)	(0.053)	(0.053)
Female × Obese	-0.211**	-0.220***	-0.242***	-0.247***	-0.262***
	(0.083)	(0.082)	(0.082)	(0.082)	(0.080)
Age	-0.070***	-0.057***	-0.062***	-0.065***	-0.112***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.017)
Female	-0.009	-0.007	-0.010	-0.010	-0.006
	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)
Fast food	0.066***	0.055***	0.043**	0.045**	0.046**
	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)
Mood general		0.111***	0.114***	0.114***	0.111***
		(0.012)	(0.012)	(0.012)	(0.012)
Standardized Patience		0.062**	0.057**	0.057**	0.036
		(0.029)	(0.028)	(0.029)	(0.030)
Bullying		-0.028	-0.037	-0.034	-0.047
		(0.087)	(0.083)	(0.083)	(0.086)
Constant	1.242***	0.714***	0.923***	0.968***	1.612***
	(0.107)	(0.120)	(0.130)	(0.140)	(0.278)
Observations	2,025	2,025	2,025	2,025	2,025
R-squared	0.039	0.063	0.066	0.068	0.140
Province FE	No	No	Yes	Yes	Yes
School FE	No	No	No	Yes	Yes
Class FE	No	No	No	No	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Standard errors are adjusted for primary sampling units clustering.

Table A5: OLS estimates for As in Spanish

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Obese	-0.066	-0.026	-0.008	-0.009	0.004
	(0.044)	(0.043)	(0.043)	(0.043)	(0.045)
Female × Obese	0.029	0.021	-0.002	0.003	0.036
	(0.097)	(0.096)	(0.097)	(0.098)	(0.100)
Age	-0.049***	-0.036***	-0.046***	-0.044***	-0.117***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.017)
Female	0.104***	0.106***	0.106***	0.107***	0.106***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Fast food	0.030	0.018	0.017	0.020	0.010
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Mood general		0.117***	0.120***	0.120***	0.116***
		(0.011)	(0.011)	(0.011)	(0.011)
Standardized Patience		0.082***	0.078***	0.079***	0.056**
		(0.027)	(0.027)	(0.027)	(0.028)
Bullying		-0.028	-0.037	-0.035	-0.051
		(0.080)	(0.081)	(0.080)	(0.087)
Constant	0.898***	0.334***	0.653***	0.624***	1.616***
	(0.105)	(0.113)	(0.124)	(0.135)	(0.275)
Observations	2,025	2,025	2,025	2,025	2,025
R-squared	0.042	0.095	0.112	0.112	0.193
Province FE No	No	Yes	Yes	Yes	
School FE	No	No	No	Yes	Yes
Class	No	No	No	No	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering.

Table A6: OLS estimates for As in English

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model
Obese	-0.160***	-0.129***	-0.109***	-0.113***	-0.097**
	(0.042)	(0.041)	(0.040)	(0.041)	(0.042)
Female × Obese	0.052	0.048	0.025	0.031	0.041
	(0.091)	(0.094)	(0.095)	(0.096)	(0.099)
Age	-0.059***	-0.048***	-0.054***	-0.055***	-0.144***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)
Female	0.090***	0.093***	0.091***	0.092***	0.085***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)
Fast food	0.103***	0.094***	0.088***	0.086***	0.077***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
Mood general		0.096***	0.102***	0.103***	0.089***
		(0.012)	(0.012)	(0.012)	(0.012)
Standardized Patience		0.042	0.049*	0.054*	0.030
		(0.029)	(0.029)	(0.029)	(0.029)
Bullying		0.026	0.030	0.024	0.022
		(0.094)	(0.090)	(0.090)	(0.091)
Constant	1.025***	0.572***	0.652***	0.665***	1.835***
	(0.011) (0.104)	(0.117)	(0.124)	(0.137)	(0.259)
Observations	2,025	2,025	2,025	2,025	2,025
R-squared	0.061	0.092	0.109	0.113	0.209
Province FE	No	No	Yes	Yes	Yes
School FE	No	No	No	Yes	Yes
Class	No	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors are adjusted for primary sampling units clustering.