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

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ABSTRACT

This paper examines the impact of childhood obesity on Spanish high school students' academic achievement and human capital accumulation. To address potential endogeneity concerns, we exploit exogenous variation in obesity within peer groups, using data from friendship networks. Specifically, we instrument individual obesity with the average body mass index of intransitive friendship triads. Our results indicate that obesity has a negative effect on academic outcomes, particularly on overall grades for girls and on cognitive abilities for both boys and girls. We also find a negative impact of obesity on girls' mathematics scores, whereas boys experience a positive effect. We identify several key drivers underlying these relationships, including class fixed-effects, which potentially reflect teacher bias, psychological well-being, and expectations related to labor market discrimination.

1. Introduction

Childhood obesity and poor body weight conditions among children and adolescents have become increasingly serious health concerns in developed countries (WHO, 2022; OECD (2024)). At the same time, investment in human capital, particularly through education, has been recognized as a key driver of long-term economic growth and development (Barro, 2001). This has sparked growing interest in the potential impact of obesity on academic achievement (Cawley, 2004; Morris, 2006, 2007). Understanding the relationship between obesity in adolescents and educational outcomes is especially important, as adolescence represents a critical period of physical, cognitive, and emotional development. Obesity during this stage is strongly linked to long-term health risks, including obesity in adults, type 2 diabetes, and cardiovascular disease. These conditions can adversely affect physical well-being, cognitive function, school attendance, and academic performance, which are crucial to shaping future employment market opportunities and socioeconomic mobility.

Beyond academic research, public policy is increasingly addressing childhood obesity and its impact on learning. For example, the Barcelona Education Consortium in Spain implements a means-tested subsidy program that ensures that children from low-income families receive balanced meals at school. According to research by Ayllón and Lado (2025), this policy significantly improves academic performance in Catalan and, to a lesser extent, in science.

In the same spirit, Giner and Placzek (2022) examined school meal programs in Chile, the United States, and France. The French case is particularly notable for its mandate of a weekly vegetarian option and collaboration between education and agriculture ministries to promote healthy eating. In the US, New York City's June 2023 initiative further exemplifies this trend by expanding nutrition education, fostering healthier school environments, and increasing access to nutritious meals, emphasizing their benefits for academic performance, attendance, and cognitive development.

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This paper uses data from high school students in the Spanish Andalusian region to examine the impact of obesity on educational performance, measured through subject-specific outcomes and standardized test scores. We explore several potential mechanisms underlying the estimated effects, including teacher bias, psychological well-being, expectations of labor market discrimination, and peer discrimination (bullying). Spain serves as a relevant case study due to the increasing prevalence of childhood obesity in recent years. It is among European countries with alarming rates, with almost 13% of children classified as obese (Sánchez-Cruz et al., 2013; Lobstein and Frelut, 2003), and approximately 30% of adolescents considered overweight.[1] A more recent study using objective anthropometric measurements found that, for the specific region of Andaluc'ia, childhood obesity affected 11% of children. In contrast, overweight affected almost a quarter of the child population during the 2015–2016 period (Sánchez-Cruz et al., 2018).

Potential endogeneity problems make it difficult to identify the causal effect of obesity on school performance. Several factors might drive such endogeneity. First, omitted variable bias is a concern as our data lack information such as family income and socioeconomic background, which likely correlate with obesity and academic outcomes. Secondly, relying on self-reported data for the height and weight of students raises measurement error issues. Finally, reverse causation presents another challenge: poor academic performance could lead to increased body weight as a coping mechanism or, conversely, cause psychological distress resulting in reduced appetite and lower body weight. To address these issues and estimate the causal effect, a key policy interest, our identification strategy leverages the exogenous variation in intransitive friendship triads' average body mass index (BMI) to instrument individual obesity. An intransitive friendship occurs in a network when there is a chain of friendships, but not all the people in the chain are directly friends with each other.[2]

Our main findings are as follows: (1) Using the experimental information available in our data, we show that self-reported weight and height measurements are reliable and comparable to objectively measured data, with no evidence of intentional misreporting. (2) Obesity negatively affects certain aspects of academic performance among high school students. This effect is particularly pronounced in girls' overall scores and cognitive abilities for both genders. Furthermore, while obesity has a negative impact on girls' mathematics grades, it is associated with a positive effect on boys. (3) Class fixed effects, which can reflect teacher bias, may be a key factor driving the negative effect on girls' overall scores. (4) The adverse psychological well-being of obese students is also a significant factor contributing to the effect on cognitive abilities, while bullying does not appear to be a relevant pathway. (5) Although not fully conclusive, our findings suggest that expectations about possible discrimination in the labor market may contribute to the negative impact of obesity on the development of human capital. This effect could be particularly relevant in sectors such as services and the creation of digital content.

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

[1] According to WHO standards, the prevalence of overweight and obesity in children is defined as the proportion with a body mass index, BMI-for-age, greater than 1 and 2 standard deviations, respectively, above the WHO Growth Reference median.

[2] In other words, you are friends with person A, and person A is friends with person B, but you are not friends with person B.

2. Literature review

A growing body of research has examined the relationship between obesity and human capital accumulation, consistently identifying obesity as a negative determinant of both educational and labor market outcomes. For example, Segal et al. (2021), in a comprehensive systematic review, conclude that childhood obesity and overweight hinder education outcomes, with effects mostly observed at older ages of exposure measurement, in high-income countries.

Early studies focused mainly on the adult population, where obesity has been shown to have a negative impact on employment and wages, particularly for women. These effects are attributed to a reduction in labor productivity as a result of poorer health or discriminatory practices (Cawley, 2004; Morris, 2006, 2007). For example, Palermo and Dowd (2012) found that obesity was associated with lower wages and reduced employment prospects, while Averett and Stifel (2010), using sibling fixed-effects models, confirmed that obesity lowers both educational attainment and labor market success, addressing some endogeneity concerns in the process. Sarrias and Blanco (2022) further demonstrated a regional variation in the effects of obesity on the labor market in Spain, suggesting that the local context may mediate these relationships.

Given the economic penalties of adult obesity, researchers have begun to investigate whether these disadvantages occur earlier in life. From a theoretical standpoint, Becker (2010) proposed that individuals may anticipate labor market discrimination and therefore adjust their investment in human capital accordingly. Empirical evidence supports this view. Cawley and Spiess (2008), analyzing data from German children, found a significant negative association between early childhood overweight and cognitive outcomes. Similarly, Datar and Sturm (2006) showed that persistent childhood obesity is associated with lower school performance, which can undermine long-term skill acquisition and future productivity.

For the US, Sabia (2007) used instrumental variables and individual fixed effects models to show that obesity and higher BMI were associated with lower GPA, although these associations weakened for non-white students when unobserved factors were accounted for. Ding et al. (2009), using genetic markers, confirmed significant gender differences, with female adolescents more negatively affected than males. Using Australian panel data, Black et al. (2015) found negative effects of obesity and BMI on boys' math and literacy scores, with magnitudes comparable to the effects of maternal education or prenatal smoking. However, when sociodemographic variables were controlled, the significance of obesity decreased, suggesting the influence of confounders.

The challenge of establishing causality has led many researchers to employ instrumental variable (IV) approaches. Kaestner and Grossman (2009) used genetic markers to find a modest but significant negative effect of obesity on wages. Sabia (2007), using sibling BMI as an instrument, reported adverse wage effects, especially among women. More recently, Iturra and Sarrias (2022) applied an IV strategy to Chilean data, finding that obesity significantly reduces educational attainment even after controlling for potential confounders. Sarrias and Blanco (2022) advanced this line of inquiry by integrating spatial econometric techniques with IV estimation to examine how the prevalence of local obesity affects individual human capital outcomes, highlighting the importance of neighborhood effects. Similarly, Shin and Shin (2008) used regional obesity rates as instruments in Korea and confirmed the negative impact of obesity on labor productivity. In addition to economic models, researchers have explored alternative mechanisms. Sabia and Rees (2015) identified psychological well-being as a key channel, accounting for approximately 30% of the observed negative association between obesity and academic performance, particularly among women. In contrast, Kaestner et al. (2011) found little evidence of a negative impact, raising concerns about reliance on self-reported height and weight and pointing to unresolved endogeneity. Scholder et al. (2012) challenged previous findings altogether, failing to detect causal effects when using genetic instruments and questioning the validity of non-genetic proxies such as parental obesity.

The medical literature supports a negative association between obesity and academic outcomes, although often without establishing causality (Geier et al., 2007; Gortmaker et al., 1993; Gutiérrez-Fisac et al., 1996). Hammond and Levine (2010), in a systematic review, emphasized the need to investigate the mechanisms behind these associations, while Cohen et al. (2013) argued in favor of experimental or quasi-experimental designs. In Spain, Gutiérrez-Fisac et al. (1996) found that lower levels of education were associated with higher obesity rates, especially among women between 1987 and 1993, although their study could not determine causality.

In conclusion, the literature demonstrates a negative relationship between obesity and the accumulation of human capital. Although there are some variations between methodologies, gender, and regional contexts, a deeper exploration of the underlying mechanisms is crucial to fully understanding the impact of obesity on human capital.

3. Data

The data used in this study come from a survey conducted as part of the *Mapeo de Competencias y Habilidades del Alumnado de Enseñanza Secundaria* (COM-PHAS) program. This initiative was led by researchers from Loyola Behavioral Lab, a behavioral economics research institute, in collaboration with the ETEA Foundation Development Institute and the Universidad Loyola Andalucia.[3]

The surveys were carried out as part of an experiment in 13 secondary schools in the Spanish region of Andalucía during the 2021–2022 school year. In particular, data were collected from schools in the provinces of Cádiz, Sevilla, Córdoba, Granada, and Málaga. Participants were recruited through collaborations with school principals, who integrated the study into their educational programs as a classroom activity, resulting in high levels of student participation. The research was implemented on-site using the Social Analysis and Network Data (SAND) platform, which ensured data privacy. The students used their tablets, computers, or smartphones to complete the questionnaire, which was available in Spanish (Vasco et al., 2024). It should be noted that the primary aims of the experiment fall outside the scope of this paper. None of the experimental designs was specifically intended to collect data on body weight or obesity. Therefore, the data set is treated as survey data rather than experimental data.[4]

The initial sample comprised 4,668 individuals aged 12 to 18, but only 2,319 provided weight and height data. After dropping individuals with missing information on the variables used in the analysis, the final data set consisted of 1,901 observations.

3.1. Obesity and human capital variables

The obesity variable was constructed using the BMI, calculated as weight in kilograms divided by the square of height in meters, based on self-reported measurements. To define obesity, we created a binary indicator equal to one if a child's BMI exceeds the age and sex specific threshold established by the World Health Organization (WHO) for childhood obesity, set at two standard deviations above the mean (Onis et al., 2007). If the BMI falls below this threshold, the variable is assigned zero.[5]

Several variables have been used as proxies for human capital, but none focus on years of schooling or school attendance, measures that are commonly used for this purpose. Instead, the variables considered are related to academic performance, including scores in different subjects and tests included in the survey. This approach should not pose analytical problems, as Hanushek and Kimko (2000) emphasize that the quality of education, measured by test scores, is at least as important, if not more so, than the quantity of education (that is, 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 self-reported A and B grades in four subjects: mathematics, Spanish (language and reading), English, and one elective chosen by the student. The A grades were defined as scores of 9–10 out of 10 in the previous school year, and the B grades as 7–9 out of 10. Each grade A was weighted at 0.25 points, while each grade B was weighted at 0.125 points. Consequently, a student achieving four A grades would receive a score of one, whereas a student with no A or B grades in these subjects during the last semester would receive a score of zero. Note that a potential concern with self-reported test scores is that they can be measured with error. If this measurement error in the dependent variable is random and uncorrelated with the independent variables, the coefficient estimates remain unbiased. However, it increases the variance of the residual term of the regression, reducing the precision of the estimates.

The second measure of human capital is the score obtained on a Cognitive Reflection Test (*CRT*), which students completed as part of the survey. This test is widely used in behavioral and experimental economics and was originally introduced by Frederick (2005). It consists of questions designed to elicit two types of responses: an intuitive, automatic response (system 1 thinking) and a more deliberate, reflective answer requiring cognitive effort (system 2 thinking).[6] A higher *CRT* score indicates greater cognitive reflection, aligning individuals more closely with the neoclassical concept of *homo economicus*. This variable is particularly relevant not only due to its novelty in the literature on this topic and its quality,[7] but also because it strongly predicts performance on standardized analytical tests such as SAT, ACT or overall GPA (Brañas-Garza et al., 2019).

The third variable is the score obtained in a test assessing *Financial abilities* (general financial mathematics).[8] This test was also administered as part of the experiment and is an accurate measure of human capital, given its strong association with current and future economic and financial decision-making.

The final set of variables used to measure human capital accumulation reflects the probability of obtaining an A grade in the last semester in different subjects, including mathematics and English. These variables are constructed as dummy variables equal to 1 if the student has received an A grade in a given subject and 0 otherwise.

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

[4] For a complete description of the recruitment process, data collection procedures, and experiment details, see Alfonso-Costillo et al. (2022).

[5] Observations with BMI values exceeding the WHO-defined maximum thresholds were treated as outliers and excluded from the analysis.

[6] This version of the CRT included three questions:

- Emilia's father has three daughters. The first two are named April and May. What is the name of the third? (*Intuitive* 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? (*Intuitive* answer: 24, correct answer: 47).
- If you are running a race and pass the person in second place, what position are you in? (*Intuitive* answer: first place, correct answer: second place).

[7] The test was administered in a controlled classroom setting under the supervision of enumerators, ensuring reliability as a measure of students' cognitive abilities.

[8] Lusardi and Mitchel (2014) provides robust evidence supporting the use of financial literacy as a precise measure of human capital, given its significant impact on economic decision-making and financial well-being. mainly because of its strong correlation with economic decision-making.

3.2. Covariates

The covariates included in the econometric analysis can be grouped into several categories. First, we include some sociodemographic variables such as age and sex, as well as the frequency of fast food consumption (measured by the number of times per week). Second, the behavioral and psychological category includes general psychological well-being (captured by a categorical variable ranging from 0 to 4), and a time preference variable based on the number of patient choices made by the child in a time discounting task (Multiple Price List, MPL). This task was performed during the experiment (see Prissé (2022) for further details). A dummy variable is also included to capture whether the child has experienced bullying. Our definition of bullying is based on both self-reports and classmates' reports. The final category accounts for unobserved heterogeneity through fixed effects at the provincial, school, and classroom levels.[9]

We now clarify the distinction between a mediator and a control variable, which is crucial for our analysis. According to Baron and Kenny (1986), a mediator (M) lies in the causal pathway between the independent variable of interest (X, in our case, obesity) and the dependent variable (Y, human capital). Specifically, X is hypothesized to influence M, which in turn affects Y, thus explaining how or why X influences Y. In contrast, a control variable (C) is not assumed to be affected by X and does not necessarily mediate any effect from X to Y. Instead, control variables are included in the analysis to account for background variation in Y, thus improving the precision of the estimated relationship between X and Y. In our study, fast food consumption and time preferences are treated as control variables, not mediators. We do not hypothesize that obesity causally influences fast food consumption or patience, nor that these variables mediate obesity's effect on human capital outcomes. Rather, they are included to account for factors that may independently influence human capital. This strategy helps reduce uncertainty in the estimated coefficients and mitigate potential confounders without implying a causal mechanism.

We were unable to include variables related to family background, such as household income or parental education, primarily due to the limited knowledge children typically have regarding these factors. The omission of these covariates presents a potential source of bias in the estimated parameters. However, this concern is mitigated to some extent by the inclusion of school fixed effects. School-level characteristics, including type (public, private, semi-private) and location, are often strongly correlated with socioeconomic background variables like income. Furthermore, using an instrumental variable approach helps to address the potential omitted variable bias that might arise from these unobserved family characteristics.

3.3. Instrumental variable

We exploit potential exogenous linear-in-means peer effects (Manski, 1993) and use the friendship network data available in our dataset to construct an instrumental variable for individual classroom-level obesity. Specifically, we instrument individual obesity using the average BMI of intransitive friendship triads within their classroom. This approach is implemented using a Two-Stage Least Squares (2SLS) estimation method.[10]

As illustrated in Fig. 1, a three-node graph (triad) in the classroom friendship network is considered intransitive if, for a given node (child) i, there exists another node k that is connected to i only through a third node j, which is directly connected to i. In this case, k is a "friend of a friend" but not a direct friend of i, as shown in panel (b). Conversely, the triad is transitive if all three nodes are directly connected, as depicted in panel (a). In our approach, the instrumental variable is derived from intransitive triads that represent "friends of friends" without a direct link.

We then construct an instrumental variable (IV) based on BMI peer effects from intransitive triads, defined as:

$$\overline{\mathrm{BMI}}_i^{FOF} = \frac{\sum_{k=1}^{\widetilde{N}_i} \mathrm{BMI}_k}{\widetilde{N}_i}, \tag{1}$$

where $\overline{\mathrm{BMI}}_i^{FOF}$ represents the average BMI of i's friends of friends who are not direct, BMI_k is the BMI of each such friend of a friend k, and $\widetilde{N}_i$ denotes the total number of i's friends of friends who are not directly connected to i (that is, the number of unique intransitive triads involving i)

This measure of peer effects is widely used in the literature when network data are available, as it helps address the so-called *reflection problem*. This problem arises when correlations between individual and group characteristics may reflect reverse causality rather than a true peer effect (see Bethencourt and Santos (2024), Bramoullé et al. (2009), Lin (2010)). Our use of this instrument follows the same reasoning. However, it is crucial to note that our primary objective is not to estimate body-weight peer effects per se, but rather to exploit the exogenous variation they provide for our analysis.[11]

The identifying assumptions underlying the use of an IV strategy are well-known. First, the instrument must be relevant, correlating with the potentially endogenous variable. Second, it must be exogenous, meaning it is not correlated with the model's error term. In our case, the relevance criterion is satisfied, as demonstrated by the significant correlation between average BMI in indirect friendship networks and individual obesity, shown in the First Stage results in Section 5. This correlation is driven by the influence of classmates on their peers' behaviors, such as eating habits and physical activity, thereby contributing to the documented network effect in the literature (see Trogdon et al. (2008), Halliday et al. (2007), Fowler and Christakis (2008)).

The second criterion, exogeneity, cannot be tested statistically. Potential correlations between the instrument and the error term of the model could arise if the average BMI of intransitive friendship triads is correlated with unobserved factors affecting academic performance (Morris, 2006). To address this concern, we control for key covariates such as age, gender, province, school, and class fixed effects, making the exogeneity assumption more plausible. Notably, including class fixed effects in both the main and first-stage equations is critical. Since the instrument is aggregated at the classroom network level (i.e., children selected friends from within their class), controlling for class fixed effects accounts for network-level unobserved heterogeneity, thereby mitigating potential biases. The average of the exogenous characteristics of intransitive friends are also included as controls in the model specification.

On the other hand, the instrument might fail to meet the exogeneity condition in the case of reverse causality. In our network-based setting, this corresponds to the reflection problem discussed earlier. To mitigate this risk, we rely on intransitive friendship triads, which help isolate peer effects by considering only indirect connections less susceptible to mutual influence. Specifically, we ensure that each "friend of a friend" effect is counted only once, preventing overemphasis on highly connected nodes that could amplify reflection. This approach assumes that feedback effects occur primarily among direct friends and diminish rapidly with increasing degrees of separation.[12]

[9] Unfortunately, we do not have data on child health, which could be a relevant mechanism to consider.

[10] For a financial economics application, see Rainone (2020). Morris (2006) and Morris (2007) adopt a related spatial approach, using the prevalence of obesity in the respondent's area of residence as an instrumental variable.

[11] This approach can be extended to incorporate higher-order structures, such as unique intransitive quadriads (friends of friends of friends who are not directly connected) and larger n-node graphs within the friendship network (see Rainone (2020)). For simplicity, we focus on this first-order approximation.

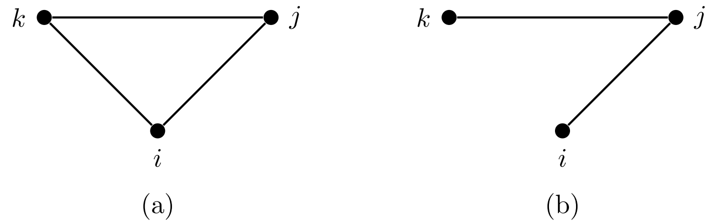

Fig. 1. Transitive and intransitive friend triads.

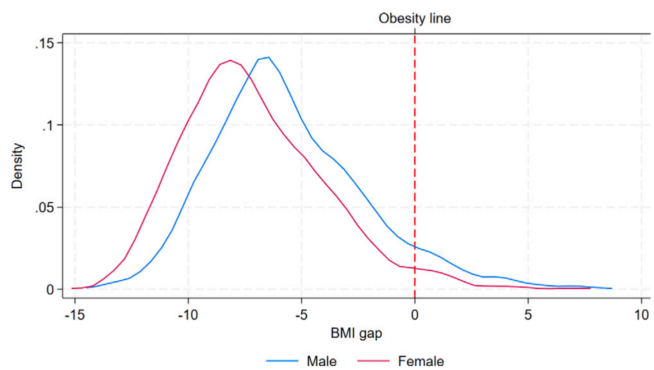

Fig. 2. Distribution of BMI gap relative to obesity thresholds.
Note: Distribution of the gap between actual BMI and obesity threshold by age and gender.

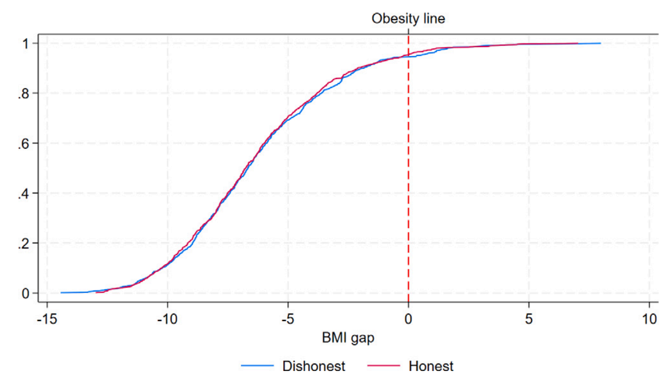

Fig. 3. Cumulative distributions of BMI gap by honesty.
Note: Kolmogorov–Smirnov test for equality of distributions ($p = 0.83$).

3.4. Descriptive statistics

Table 1 presents descriptive statistics for the full sample and by obesity status, including body weight measures, human capital outcomes, and other covariates. Consistent with previous literature, childhood obesity shows a relatively high prevalence in our data, affecting 5% of the sample.[13] Our unconditional analysis shows that, at conventional levels of statistical significance, obese children perform worse than their non-obese peers across all educational outcomes, except for mathematics, where differences are not statistically significant. Furthermore, only about a quarter of the obese children in our sample are female, compared to nearly half among the non-obese children. Obese children also report higher rates of fast food consumption and more frequent experiences of bullying.

Fig. 2 shows the distribution of BMI within the sample. Given that BMI distributions typically vary by age and gender in children and adolescents, we present a standardized comparative measure. This measure reflects the gap between each child's actual BMI and the obesity threshold specific to their age and gender. As observed in larger samples, the distribution appears to be approximately normal, with a mean in line with typical BMI values for children of this age (around 20).

3.5. Measurement error in Self-reported BMI

A potential concern with self-reported weight and height data is that children can intentionally provide inaccurate information, reporting a lower (or higher, depending on their physical condition or self-perception) BMI than their actual values. If this occurs, we would expect to observe differences in BMI between children who report honestly and those who do not, potentially distorting the distribution. Such discrepancies could shift the distribution to the left, to the right, or towards the mean, thereby exacerbating the measurement error bias.

To explore this possibility, Fig. 3 compares the BMI distributions of children who report honestly and those who do not, using Kolmogorov–Smirnov tests for equality of distributions. A failure to reject the null hypothesis of equal distributions would support the idea that, despite potential unintentional errors, self-reported weight and height data can serve as reasonable proxies for actual values.

The variable *Honesty* was measured using a task in which the children were randomly assigned a colored number to memorize, each associated with a hypothetical payoff. They were then asked to identify the color of the number they had received, with payoffs displayed next to the response options. No restrictions prevented participants from claiming several different colors with a higher pay-off. The number assigned and the answer given were recorded, and a dummy variable for honesty was created, taking the value 1 if the child answered honestly and 0 otherwise.

In this context, dishonesty is defined as a harmless "white lie", such as deliberately misreporting one's height or weight. We expect that children who were dishonest in the task are more likely to misreport their weight and height. Our analysis shows that the BMI distributions of honest and dishonest children are statistically identical (the p-value of the test is 0.83). This finding suggests that intentional misreporting is not a significant problem and supports the validity of using self-reported weight and height data in our analysis.

Another concern with self-reported BMI measures is that obese children may avoid reporting their weight or height due to shame or fear of stigma, potentially introducing selection bias.[14] This issue is often overlooked in the literature or addressed by assuming that

[12] This assumption is supported by Bethencourt and Santos (2024), who estimate peer effects on academic achievement using friends of friends from different academic years as an instrument. Their IV results and endogeneity tests suggest that, while OLS estimates may be consistent, measurement error is a more significant concern than reverse causality, evidenced by the larger 2SLS coefficients relative to OLS estimates.

[13] Sánchez-Cruz et al. (2013) report an overall childhood obesity prevalence of 11% in a representative sample of Andalusian children, based on objective measurements. However, for the 14–15 age group, corresponding precisely to the average age of our sample, the estimated prevalence is 4.6%, which closely aligns with our observed rate of 5%.

[14] Children had the option to choose whether to report this information during the survey.

Table 1
Summary statistics.

Variables	All	Boys	Girls	Obese boys	Non-obese boys	Obese girls	Non-obese girls
BMI	20.12	20.28	19.93	27.50***	19.74***	29.09***	19.66***
	(3.31)	(3.41)	(3.18)	(2.38)	(2.80)	(2.03)	(2.78)
Obese	0.05	0.07	0.03	–	–	–	–
	(0.22)	(0.26)	(0.17)	–	–	–	–
Overweight	0.19	0.22	0.16	–	–	–	–
	(0.39)	(0.41)	(0.37)	–	–	–	–
Score	0.26	0.24	0.29	0.23	0.24	0.19**	0.29**
	(0.22)	(0.19)	(0.25)	(0.20)	(0.19)	(0.13)	(0.25)
CRT	0.53	0.55	0.51	0.48**	0.55**	0.41**	0.52**
	(0.26)	(0.26)	(0.26)	(0.23)	(0.27)	(0.26)	(0.26)
Financial abilities	0.40	0.45	0.35	0.40	0.45	0.23**	0.35**
	(0.28)	(0.28)	(0.26)	(0.27)	(0.28)	(0.23)	(0.26)
As in Maths	0.31	0.32	0.31	0.40	0.31	0.12**	0.31**
	(0.46)	(0.47)	(0.46)	(0.49)	(0.46)	(0.33)	(0.46)
As in English	0.31	0.26	0.37	0.15**	0.27**	0.24	0.37
	(0.46)	(0.44)	(0.48)	(0.36)	(0.44)	(0.44)	(0.48)
Female	0.46	–	–	–	–	–	–
	(0.50)	–	–	–	–	–	–
Age	13.99	14.04	13.92	13.61***	14.08***	14.44**	13.90**
	(1.35)	(1.39)	(1.30)	(1.30)	(1.39)	(1.50)	(1.29)
Fast food	0.72	0.74	0.70	0.81	0.73	0.76	0.69
	(0.45)	(0.44)	(0.46)	(0.40)	(0.44)	(0.44)	(0.46)
Psychological mood	2.91	2.92	2.90	2.64***	2.94***	2.56**	2.91**
	(0.85)	(0.87)	(0.83)	(1.04)	(0.85)	(0.96)	(0.82)
Patience	0.56	0.54	0.57	0.59	0.54	0.55	0.57
	(0.34)	(0.34)	(0.34)	(0.37)	(0.34)	(0.33)	(0.34)
Bullying	0.01	0.01	0.02	0.06***	0.00***	0.00	0.02
	(0.11)	(0.09)	(0.13)	(0.23)	(0.06)	(0.00)	(0.13)
N	1901	1029	872	72	957	25	847

Notes: Standard deviations in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for differences in mean by obesity condition. *Overweight* and *obese* are calculated as the proportion of children and adolescents with a body mass index, BMI-for-age, greater than 1 and 2 standard deviations, respectively, above the WHO Growth Reference median.

missing responses are randomly distributed or explained by observable characteristics. However, Dutz et al. (2021) find that such selection can introduce a substantial bias. To investigate this, Table 2 compares the average academic outcomes between respondents who reported their weight and height and those who did not. The results suggest that nonrespondents perform worse on average in all human capital measures that were considered. If a larger proportion of obese children are among the nonrespondents, this suggests that the effects of interest, if any, may be underestimated.

Finally, since the friendship network data are self-reported by students, there may be concerns about potential measurement errors that could threaten the exogeneity of our instrument. To address this issue, we tested for differences in the distribution of four centrality measures in the friendship network across levels of honesty, following the approach shown in Fig. 3. Specifically, we considered: (i) out-degree centrality (the number of friends an individual reports), (ii) betweenness centrality (based on the shortest paths between nodes), (iii) the clustering coefficient (which captures the extent to which an individual's friends are also friends with one another), and (iv) supported degree (a measure reflecting friendship support through mutual connections). We do not find statistically significant differences in the distribution of any of these measures by honesty (see Fig. A.1), suggesting that any potential measurement error in reported friendships is unlikely to compromise the exogeneity of our instrument.

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:

$$h_i = \beta_0 + \beta_1 Obese_i + \beta_2 Obese_i \times Female_i + \beta_3 Female_i + \beta_4' X_i + \theta_p + \delta_s + \zeta_c + \epsilon_i, \quad (2)$$

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

Variables	Respondents	Non-respondents	Difference in means (p-value)
Score	0.26	0.25	0.06
	(0.22)	(0.20)	
CRT	0.53	0.47	0.00
	(0.26)	(0.28)	
Financial abilities	0.40	0.31	0.00
	(0.28)	(0.27)	
As in Maths	0.31	0.23	0.00
	(0.46)	(0.42)	
As in English	0.31	0.27	0.07
	(0.46)	(0.45)	
N	1901	660	

Notes: Standard deviations in parentheses.

where h_i represents a measure of human capital for child i. The variable $Obese_i$ is a dummy variable that equals 1 if the child is obese and 0 otherwise. Similarly, $Female_i$ is a dummy that takes the value 1 if the child is female and 0 otherwise. The vector X_i contains sociodemographic, 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.[15]

The coefficients of interest in our model are β_1 and β_2. Specifically, β_1 represents the average impact of obesity on academic achievement, while β_2 captures the differential effect of obesity between girls and boys. We first estimate this model using Ordinary Least Squares (OLS).

[15] Although the relationship of interest for binary human capital measures, such as obtaining an A grade, is non-linear, we use linear probability models (LPM) for simplicity.

Table 3
OLS estimates for general scores.

	(1)	(2)	(3)	(4)	(5)
Obese	−0.020	−0.008	−0.007	−0.020	−0.008
	(0.024)	(0.025)	(0.024)	(0.025)	(0.025)
Female × Obese	−0.074**	−0.047	−0.075**	−0.043	−0.048
	(0.036)	(0.038)	(0.036)	(0.038)	(0.038)
Female	0.047***	0.051***	0.048***	0.049***	0.052***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)
Psy. mood		0.033***	0.038***		0.033***
		(0.006)	(0.006)		(0.006)
Bullying (intersection)		0.015	−0.004	−0.003	
		(0.044)	(0.041)	(0.043)	
Constant	0.533***	0.818***	0.338***	1.058***	0.819***
	(0.058)	(0.128)	(0.064)	(0.118)	(0.128)
N	1901	1901	1901	1901	1901
R^2	0.045	0.151	0.069	0.137	0.151
Class FE	NO	YES	NO	YES	YES
Δ% Obese	–	–	−14.29	60.00	0.00
Δ% Female × Obese	–	–	37.33	−9.30	2.08

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include province fixed-effects, school fixed-effects, age, fast food consumption, and time preferences. Δ% is calculated as: (Coeff. without mechanism − Coeff. with mechanism)/abs(Coeff. without mechanism).

Table 4
OLS estimates for CRT.

	(1)	(2)	(3)	(4)	(5)
Obese	−0.069**	−0.052*	−0.064**	−0.059*	−0.053*
	(0.029)	(0.031)	(0.029)	(0.031)	(0.031)
Female × Obese	−0.051	0.007	−0.048	0.009	0.008
	(0.059)	(0.065)	(0.059)	(0.065)	(0.065)
Female	−0.026**	−0.024*	−0.027**	−0.025**	−0.024*
	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)
Psy. mood		0.018**	0.023***		0.018**
		(0.008)	(0.007)		(0.008)
Bullying (intersection)		−0.011	−0.012	−0.022	
		(0.062)	(0.055)	(0.061)	
Constant	0.249***	1.079***	0.104	1.213***	1.079***
	(0.075)	(0.207)	(0.084)	(0.198)	(0.207)
N	1901	1901	1901	1901	1901
R^2	0.026	0.153	0.042	0.150	0.153
Class FE	NO	YES	NO	YES	YES
Δ% Obese	–	–	18.75	11.86	1.89
Δ% Female × Obese	–	–	114.58	−22.22	−12.50

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include province fixed-effects, school fixed-effects, age, fast food consumption, and time preferences. Δ% is calculated as: (Coeff. without mechanism − Coeff. with mechanism)/abs(Coeff. without mechanism).

To investigate the potential mechanisms underlying our findings, we re-estimate Eq. (2) while excluding each theorized pathway through which obesity might affect human capital accumulation. These pathways include class fixed effects, psychological mood, and bullying. By comparing the OLS coefficient of obesity in these restricted models to the one obtained in the full specification (which includes all covariates), we assess the relative magnitude of omitted variable bias and highlight the extent to which each potential driver mediates the relationship between obesity and human capital accumulation (Heckman and Pinto, 2015).

For OLS estimates to be consistent, the error term must be uncorrelated with the main variable of interest $Obese_i$. However, even after controlling for observed variables that could be correlated with obesity, endogeneity concerns remain. Consequently, the OLS estimates from Eq. (2) may not capture the causal effect of obesity on academic outcomes. Several factors contribute to this endogeneity:

First, as discussed above, the lack of data on family income or socioeconomic background could lead to omitted variable bias, as unobserved factors may be correlated with obesity and academic performance. Although school fixed effects partially address this issue, they may not fully eliminate it. Second, self-reported weight and height data may contain measurement errors. Although the BMI distribution appears normal and there is no statistical evidence of systematic differences in reporting between honest and dishonest children, there is uncertainty about whether self-reports accurately reflect true values. Finally, there may be reverse causation, where low academic achievement could lead to increased body weight, or vice versa.

To address these endogeneity concerns, we use an IV estimation strategy. Specifically, we estimate Eq. (2) using 2SLS, where individual obesity ($Obese_i$) is instrumented using the average BMI of intransitive friendship triads (friends of friends who are not direct friends), denoted $\overline{\text{BMI}}_i^{FOF}$ in Eq. (1). The 2SLS estimates are interpreted as the Local Average Treatment Effects (LATE), or the effect on compliers, that is, individuals whose behavior changes in response to variations in the instrument (Imbens and Angrist, 1994).

5. Estimation results

5.1. OLS estimates and potential mechanisms

The main results of the OLS regression for each educational outcome are presented in Tables 3 to 7. These tables report the coefficients for the average impact of obesity ($Obese$) and its differential effect for girls ($Female \times Obese$). Our initial approach involved the use of BMI as a continuous variable, including a quadratic term and interactions with gender. However, these specifications did not yield statistically significant results. We also tested the effect of a dummy variable for being overweight, which did not show a significant impact on our measures of human capital. This result contrasts with those of Segal et al. (2021), who conclude that overweight has a statistically significant negative impact on various dimensions of human capital in high-income countries.[16] These findings suggest that only extreme weight, captured by the obesity category, appears to be associated with differences in human capital outcomes. The first column in Tables 3 to 7 present the results for a baseline specification without any mediator included. Then, we highlight the impact of potential mediating variables such as class fixed effects, psychological mood, and bullying. Our objective is to assess the importance of these mediators, which are often considered key channels in the theoretical literature linking obesity to academic achievement. To do so, we first estimate a fully specified model that includes all mediators (see the second column in Tables 3 to 7). Then, we estimate alternative specifications by excluding one mediator at a time to evaluate its contribution.[17] We adjust the standard errors accordingly to account for the potential non-independence of observations within groups. We have added a row to the tables showing how the coefficients change when each mechanism is excluded. Specifically, we report the percentage change in the coefficient for boys, as well as the percentage change in the coefficient capturing the differential effect for girls.[18]

The results in Table 3 indicate that when all controls are included, obesity does not have a significant effect on the overall scores for boys or girls (column (2)). For boys, the effect remains non-significant both before and after including class fixed effects. However, for girls,

[16] This discrepancy may be due to differences in sample composition, empirical strategy, or country-specific contexts, and underscores the need for further research using harmonized methodologies.

[17] The full set of estimates is available upon request.

[18] Table A.1 in the Appendix presents the correlations between each potential mediator and the obesity variable. As shown, both unconditionally and after controlling for covariates, there is a significant relationship between them.

Table 5
OLS estimates for financial abilities.

	(1)	(2)	(3)	(4)	(5)
Obese	−0.032	−0.009	−0.021	−0.019	−0.009
	(0.033)	(0.029)	(0.032)	(0.029)	(0.029)
Female × Obese	−0.102*	−0.042	−0.102*	−0.039	−0.043
	(0.054)	(0.054)	(0.056)	(0.054)	(0.054)
Female	−0.088***	−0.093***	−0.088***	−0.095***	−0.093***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Psy. mood		0.030***	0.035***		0.030***
		(0.007)	(0.007)		(0.007)
Bullying (intersection)		0.008	0.001	−0.009	
		(0.058)	(0.057)	(0.057)	
Constant	−0.137*	0.839***	−0.325***	1.060***	0.840***
	(0.076)	(0.215)	(0.082)	(0.207)	(0.215)
N	1901	1901	1901	1901	1901
R^2	0.079	0.200	0.094	0.192	0.200
Class FE	NO	YES	NO	YES	YES
Δ% Obese	–	–	57.14	52.63	0.00
Δ% Female × Obese	–	–	58.82	−7.69	2.33

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include province fixed-effects, school fixed-effects, age, fast food consumption, and time preferences. Δ% is calculated as: (Coeff. without mechanism – Coeff. with mechanism)/abs(Coeff. without mechanism).

Table 6
OLS estimates for As in mathematics.

	(1)	(2)	(3)	(4)	(5)
Obese	0.054	0.121**	0.098*	0.083	0.118**
	(0.058)	(0.056)	(0.055)	(0.058)	(0.055)
Female × Obese	−0.234***	−0.257***	−0.245***	−0.243***	−0.253***
	(0.087)	(0.081)	(0.086)	(0.083)	(0.081)
Female	−0.014	−0.003	−0.009	−0.009	−0.003
	(0.021)	(0.022)	(0.021)	(0.022)	(0.022)
Psy. mood		0.113***	0.116***		0.113***
		(0.013)	(0.012)		(0.013)
Bullying (intersection)		−0.047	−0.033	−0.110	
		(0.085)	(0.083)	(0.087)	
Constant	1.408***	1.451***	0.835***	2.271***	1.448***
	(0.122)	(0.281)	(0.135)	(0.264)	(0.281)
N	1901	1901	1901	1901	1901
R^2	0.068	0.192	0.113	0.156	0.192
Class FE	NO	YES	NO	YES	YES
Δ% Obese	–	–	23.47	45.78	2.54
Δ% Female × Obese	–	–	−4.90	−5.76	−1.58

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include province fixed-effects, school fixed-effects, age, fast food consumption, and time preferences. Δ% is calculated as: (Coeff. without mechanism – Coeff. with mechanism)/abs(Coeff. without mechanism).

obesity is associated with a negative impact when class fixed effects are excluded (column (3)). Specifically, the estimated coefficient for the differential effect for girls decreases by 37% (from −0.075 to −0.047) and loses significance once class fixed effects are introduced. This suggests that unobservable class-level characteristics may explain much of the observed negative relationship. A plausible explanation, as proposed by Sabia (2007), is teacher-specific discrimination against obese girls. Although we cannot directly control for teacher fixed effects, we argue that the stronger effect observed when class fixed effects are omitted may be due to such discrimination.[19]

[19] 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 considers the quality of the child–teacher relationship in their analysis.

Table 7
OLS estimates for As in English.

	(1)	(2)	(3)	(4)	(5)
Obese	−0.145***	−0.100**	−0.106**	−0.133***	−0.099**
	(0.045)	(0.045)	(0.044)	(0.046)	(0.045)
Female × Obese	0.036	0.046	0.030	0.057	0.043
	(0.097)	(0.104)	(0.101)	(0.102)	(0.104)
Female	0.093***	0.095***	0.097***	0.089***	0.095***
	(0.022)	(0.021)	(0.021)	(0.022)	(0.021)
Psy. mood		0.096***	0.112***		0.095***
		(0.012)	(0.012)		(0.012)
Bullying (intersection)		0.037	0.029	−0.017	
		(0.092)	(0.090)	(0.094)	
Constant	1.087***	1.954***	0.534***	2.649***	1.957***
	(0.122)	(0.267)	(0.135)	(0.247)	(0.267)
N	1901	1901	1901	1901	1901
R^2	0.076	0.219	0.117	0.193	0.219
Class FE	NO	YES	NO	YES	YES
Δ% Obese	–	–	5.66	24.81	−1.01
Δ% Female × Obese	–	–	53.33	−19.30	6.98

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include province fixed-effects, school fixed-effects, age, fast food consumption, and time preferences. Δ% is calculated as: (Coeff. without mechanism – Coeff. with mechanism)/abs(Coeff. without mechanism).

For other outcomes, including class fixed effects, neither changes the lack of significance of obesity's effect nor explains a smaller part of the relationship (see tables below). Teacher discrimination is likely to be more relevant for general scores as they are collected and assessed directly by teachers. In contrast, CRT and financial abilities scores, derived from tests rather than teacher evaluations, are less susceptible to teacher bias. This pattern supports the hypothesis that teacher discrimination against obese girls may explain the loss of significance for general scores after controlling for class fixed effects

Columns (4) to (5) in Table 3 further show that omitting a proxy for mental health or bullying does not alter the non-significant effect of obesity. This suggests that none of these factors are relevant mechanisms in explaining the relationship between obesity and general scores.

The results in the second column of Table 4 show that both obese boys and girls have lower CRT scores than their non-obese peers, with an average reduction of 0.52 points out of 10. This negative relationship remains statistically significant when class fixed effects are excluded, supporting the hypothesis of teacher discrimination, as CRT scores were derived from a test administered independently of teacher evaluations.

Other potential mediators have minimal effect on OLS estimates of the impact of obesity on CRT scores. For example, including a mental health proxy reduces the negative effect by almost 19% (from −0.064 to −0.052) but does not change the lack of statistical significance. These findings align with previous studies (Sabia and Rees 2015, Cawley 2004) and suggest a negative conditional correlation between obesity and psychological well-being, which can affect motivation and academic engagement.

Regarding bullying (column (5)), including this variable does not produce statistically significant effects on CRT scores or other outcomes, suggesting that bullying is not a key mechanism in explaining the impact of obesity on CRT scores or any of the outcomes considered (see tables below).

For financial abilities (Table 5), only a marginally significant negative association is obtained for girls when class-fixed effects are excluded. Again, this suggests that unobservable characteristics at a class level may mediate this relationship. However, the teacher discrimination hypothesis aligns more closely with the findings for overall scores, as financial skills were evaluated during the experiment rather than by teachers. Additionally, omitting the rest of the potential mediators does

Table 8
2SLS estimates for cognitive and educational measures.

	(1) Score	(2) CRT	(3) Financial abilities	(4) Mathematics	(5) English
Panel A: Two Stage Least Squares					
Obese	0.829	−0.652	0.689	0.701	−0.819
	(0.813)	(0.855)	(0.912)	(1.423)	(1.417)
Female × Obese	−1.082	0.305	−1.202	−0.765	0.194
	(0.876)	(0.916)	(0.980)	(1.537)	(1.531)
Constant	−0.479	−0.331	−0.954	0.783	2.967**
	(0.763)	(0.839)	(0.924)	(1.286)	(1.431)
N	1901	1901	1901	1901	1901
All controls	YES	YES	YES	YES	YES
Hausman F-statistic	1.213	1.234	2.726*	0.129	1.623
Panel B: First stage for Obese and Female × Obese					
$\overline{\text{BMI}}$ (intransitive friend triads)	0.023**	0.023**	0.023**	0.023**	0.023**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Female × $\overline{\text{BMI}}$	0.024***	0.024***	0.024***	0.024***	0.024***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Panel C: OLS					
Obese	−0.008	−0.052*	−0.009	0.121**	−0.100**
	(0.025)	(0.031)	(0.029)	(0.056)	(0.045)
Female × Obese	−0.047	0.007	−0.042	−0.257***	0.046
	(0.038)	(0.065)	(0.054)	(0.081)	(0.104)
All controls	YES	YES	YES	YES	YES

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Controls include gender, age, fast food consumption, psychological mood, time preferences (number of patient choices), bullying, variables capturing intransitive friend triad averages for the latter six, along with province, school, and class fixed effects.
First Stage models in Panel B include all controls.

Table A.1
Impact of obesity on mediators.

	(1) Psyc. mood	(2) Psyc. mood	(3) Bullying	(4) Bullying
Obese	−0.304**	−0.403***	0.051*	0.053*
	(0.125)	(0.122)	(0.027)	(0.027)
Female × Obese	−0.045	0.117	−0.069**	−0.069**
	(0.228)	(0.222)	(0.027)	(0.028)
Female	−0.033	−0.058	0.014***	0.012***
	(0.039)	(0.039)	(0.005)	(0.005)
Time preferences		0.074		0.010
		(0.059)		(0.007)
Age		−0.121***		−0.002
		(0.017)		(0.002)
Fast food consumption		0.075*		−0.000
		(0.044)		(0.005)
Constant	2.943***	4.679***	0.004**	0.041
	(0.028)	(0.231)	(0.002)	(0.031)
N	1901	1901	1901	1901
R^2	0.007	0.061	0.010	0.021

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include province fixed-effects and school fixed-effects.

not change the nonsignificant correlation between obesity and financial abilities for boys and girls.

In the analysis of achieving A grades in mathematics (Table 6), the OLS estimates from the Linear Probability Model consistently show a positive impact of obesity on the likelihood of boys attaining an A grade, while for girls, the effect is negative. Specifically, in the fully controlled model, the probability that obese boys receive an A increases by 12.1 percentage points (pp), whereas for obese girls, it decreases by 13.6 pp. Among the potential mediators, only the mental health proxy significantly alters the impact for boys. When included, the coefficient increases by about 46% (from a non-significant 0.083 to 0.121). 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 may suggest that the learning curve in mathematics is such that improving academic performance becomes more costly for obese boys in terms of weight management compared to other subjects.

For English (Table 7), obesity is associated with a lower probability of obtaining an A grade for both boys and girls, which reduces their likelihood approximately by 10 pp. compared to their non-obese peers. The inclusion of class fixed effects does not significantly alter the estimated coefficients. However, psychological well-being emerges as an important mediator: controlling for this variable reduces the estimated negative effect of obesity on the likelihood of achieving an A in English by close to 25% (from −0.133 to −0.100).

Finally, we examine whether expectations of labor market discrimination contribute to the associations discussed above. The theory suggests that people who anticipate discrimination can reduce their commitment to certain academic activities and adjust their human capital investments accordingly (Becker, 2010, 2009). To explore this, we estimate Linear Probability Models to assess the relationship between obesity and the likelihood of boys and girls wanting to work in various sectors.[20] If obese children are less inclined to pursue sectors with prevalent discrimination, this could indicate that they allocate fewer resources and less time to academic pursuits, influenced by their perceptions of the labor market. Fig. 4 shows the estimated coefficients and confidence intervals of these regressions.

Most of the coefficients in Fig. 4 are not statistically significant, suggesting that there is limited evidence to support expectations of discrimination in the labor market as a potential mechanism. This may be partly explained by the smaller sample size of 518 observations. However, there are some notable findings. Obese girls are 5 pp less likely to express interest in working in the services sector, 10 pp less

[20] The survey includes questions about sector preferences for work.

Table A.2
2SLS estimates for general scores.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two Stage Least Squares						
Obese	0.381	0.279	0.012	0.252	0.381	0.829
	(0.391)	(0.363)	(0.341)	(0.477)	(0.497)	(0.813)
Female × Obese	−0.633	−0.524	−0.299	−0.506	−0.636	−1.082
	(0.523)	(0.494)	(0.482)	(0.603)	(0.623)	(0.876)
Age	−0.018***	−0.014***	−0.059***	−0.058***	−0.058***	−0.055***
	(0.005)	(0.005)	(0.010)	(0.011)	(0.012)	(0.015)
Female	0.079**	0.073**	0.053*	0.071*	0.080*	0.120*
	(0.033)	(0.032)	(0.032)	(0.042)	(0.043)	(0.066)
Fast food consumption	0.031***	0.029***	0.024**	0.021*	0.019*	0.015
	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.016)
Time preferences	0.036**	0.035**	0.024	0.019	0.015	0.004
	(0.016)	(0.016)	(0.017)	(0.018)	(0.019)	(0.027)
Psyc. mood		0.041***	0.033***	0.037***	0.040***	0.045***
		(0.008)	(0.008)	(0.011)	(0.011)	(0.017)
Bullying		−0.045	0.007	−0.027	−0.046	−0.105
		(0.071)	(0.069)	(0.087)	(0.092)	(0.143)
Constant	0.427***	0.263**	0.162	0.093	0.040	−0.479
	(0.094)	(0.110)	(0.113)	(0.155)	(0.163)	(0.763)
N	1901	1901	1901	1901	1901	1901
Controls for intransitive friend triads	NO	NO	YES	YES	YES	YES
Province FE	NO	NO	NO	YES	YES	YES
School FE	NO	NO	NO	NO	YES	YES
Class FE	NO	NO	NO	NO	NO	YES
Panel B: First stage for Obese and Female × Obese						
$\overline{\text{BMI}}$ (intransitive friend triads)	0.019**	0.020**	0.023***	0.022***	0.024***	0.023**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Female × $\overline{\text{BMI}}$	0.026***	0.026***	0.025***	0.024***	0.023***	0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

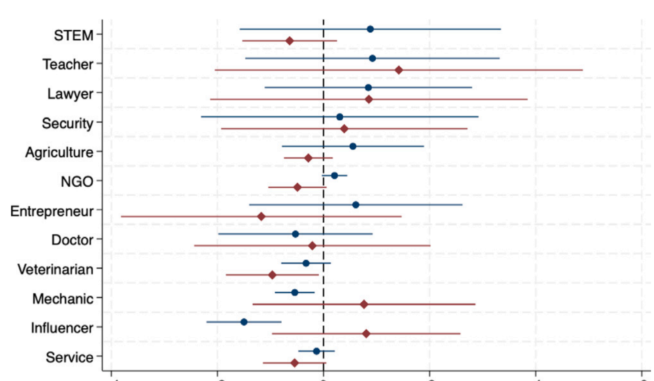

Fig. 4. Associations between obesity and preferences for different jobs.
Notes: Blue dotted estimates are for boys, and red diamond-shaped estimates are for girls. All coefficients are obtained by regressing each type of job on obesity, its interaction with gender, all the controls specified above, and province, school, and class fixed effects.

likely to aspire to be veterinarians, and 5 pp less likely to work for an NGO (all significant at the 10% level). Obese boys are 5 pp less likely to pursue careers as mechanics and 16 pp less likely to aspire to become YouTubers or influencers.

Existing literature suggests that jobs involving more direct customer interaction, such as in the service sector, often experience higher levels of discrimination, particularly for women (Bellizzi and Hasty, 1998; Everett, 1990; Harper, 2000). This could explain why obese girls are less inclined towards the service sector, while obese boys may avoid roles with high public exposure, such as content creators. Furthermore, Baum and Ford (2004) found evidence of discrimination against obese workers in the craft sector, which aligns with a lower interest in mechanics. However, some argue that this is due to statistical discrimination or productivity effects.

If obese children avoid certain sectors due to perceived discrimination, this could be an important mechanism that contributes to the negative impact of obesity on human capital accumulation. They may devote fewer resources to the acquisition of relevant knowledge in these sectors, which could potentially lead to lower levels of academic achievement.

5.2. IV estimates

Previous OLS estimates have a causal interpretation only if the unobserved factors in the model are not correlated with obesity. Even after controlling for observables, endogeneity may still arise due to unobserved variables, reverse causality, or measurement errors. This section examines this issue and addresses potential endogeneity in the full specification using an IV approach.

Table 8 presents the 2SLS estimates for the different measures of human capital. The table reports the coefficients for the variables of interest, Obese and its interaction with Female, while the full set of estimates is in the appendix. We use the average BMI of intransitive friendship triads (i.e., friends of friends who are not directly connected) as the instrumental variable for individual obesity. This instrument remains highly relevant even after accounting for province, school, and,

Table A.3
2SLS estimates for CRT.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two Stage Least Squares						
Obese	0.511	0.447	−0.259	−0.383	−0.456	−0.652
	(0.579)	(0.552)	(0.475)	(0.635)	(0.647)	(0.855)
Female × Obese	−0.730	−0.662	−0.004	0.105	0.113	0.305
	(0.737)	(0.711)	(0.642)	(0.778)	(0.791)	(0.916)
Age	0.024***	0.027***	−0.079***	−0.079***	−0.079***	−0.060***
	(0.007)	(0.008)	(0.016)	(0.017)	(0.017)	(0.018)
Female	0.013	0.010	−0.044	−0.052	−0.054	−0.061
	(0.046)	(0.045)	(0.041)	(0.052)	(0.053)	(0.068)
Fast food consumption	0.011	0.009	0.009	0.011	0.013	0.020
	(0.016)	(0.016)	(0.014)	(0.015)	(0.015)	(0.018)
Time preferences	0.073***	0.073***	0.080***	0.083***	0.085***	0.085***
	(0.021)	(0.020)	(0.021)	(0.023)	(0.024)	(0.029)
Psyc. mood		0.030**	0.013	0.011	0.009	0.007
		(0.012)	(0.011)	(0.014)	(0.014)	(0.018)
Bullying		−0.089	0.026	0.043	0.055	0.073
		(0.103)	(0.094)	(0.115)	(0.119)	(0.146)
Constant	0.125	0.003	0.090	0.173	0.084	−0.331
	(0.131)	(0.160)	(0.151)	(0.200)	(0.206)	(0.839)
N	1901	1901	1901	1901	1901	1901
Controls for intransitive friend triads	NO	NO	YES	YES	YES	YES
Province FE	NO	NO	NO	YES	YES	YES
School FE	NO	NO	NO	NO	YES	YES
Class FE	NO	NO	NO	NO	NO	YES
Panel B: First stage for Obese and Female × Obese						
$\overline{\text{BMI}}$ (intransitive friend triads)	0.019**	0.020**	0.023***	0.022***	0.024***	0.023**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Female × $\overline{\text{BMI}}$	0.026***	0.026***	0.025***	0.024***	0.023***	0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

crucially, class fixed effects in the model specification (see the First Stage estimates in panel B of Table 8).[21]

Unfortunately, because we use a single instrument, we cannot formally test the exogeneity condition. However, Section 3.3 of the paper provides a detailed discussion that justifies our assumption that the instrument is plausibly exogenous. Our identification strategy relies on the assumption that, after controlling for class fixed effects and a rich set of individual and contextual covariates, the mean BMI of intransitive friends does not exert a direct effect on the outcome variable (educational outcomes), but only influences it indirectly through individual obesity. We consider the use of intransitive friends (i.e., friends of friends who are not directly connected to the individual) to be particularly helpful in reinforcing the plausibility of exogeneity, as it reduces the likelihood of direct peer influence or reflection problems. Furthermore, we include not only class fixed effects but also covariates related to the characteristics of intransitive friends, which helps mitigate the risk that unobserved common factors, correlated with both the instrument and the outcome, bias our estimates.

Table 8 shows no significant effect of obesity on any measure of human capital for boys or girls once all observables and potential endogeneity are taken into account. However, the Hausman test which assesses the null hypothesis of exogeneity of obesity. Suggests that we cannot reject the hypothesis that the OLS estimates from the full model are consistent for general scores, CRT, and the probability of obtaining an A grade in mathematics. Therefore, we consider the OLS estimates in column (1) of Tables 3, 4, and 6 as our preferred estimates for these outcomes. As discussed previously, the OLS results suggest that (i) obesity has no significant effect on general scores for boys, while for girls, unobserved class-level characteristics explain much of the estimated negative relationship; (ii) obesity has a negative impact on cognitive abilities for both boys and girls, regardless of the inclusion of class-fixed effects; and (iii) there is a positive impact of obesity on the likelihood of attaining an A grade in mathematics for boys, but has a negative effect for girls, with mental health acting as an important mediator in this relationship for boys. For financial abilities and the probability of attaining an A in English, the Hausman test marginally rejects the null hypothesis of exogeneity of obesity, making the 2SLS estimates our preferred results, indicating no significant effect.[22]

6. Conclusions

This study examines the impact of obesity on the accumulation of human capital and explores the potential mechanisms driving these effects. Specifically, it analyzes the role of class fixed effects and its potential relationship with teacher discrimination, psychological well-being, bullying (peer discrimination), and expectations regarding labor market discrimination as factors driving the estimated impacts. Using cross-sectional data from an experiment conducted in secondary schools in different localities of Andalucía (Spain), we exploit the exogenous variation stemming from obesity within peer groups, using data from friendship networks. We provide evidence suggesting that

[21] We also include the average of exogenous variables of intransitive friends to control for potential unobservables correlated with weight at the network level.

[22] Our findings that IV estimates are not significant are in line with Scholder et al. (2012), who challenged the view that obesity negatively affects academic performance. They were unable to find a causal effect using two genetic markers that influence obesity, suggesting that non-genetic instruments used in other studies (e.g., parental obesity) are not valid instruments due to their potential correlation with other child and family characteristics.

Table A.4
2SLS estimates for financial abilities.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two Stage Least Squares						
Obese	1.112	1.002	0.303	−0.063	0.096	0.689
	(0.750)	(0.695)	(0.526)	(0.663)	(0.669)	(0.912)
Female × Obese	−1.358	−1.241	−0.600	−0.297	−0.476	−1.202
	(0.934)	(0.873)	(0.691)	(0.806)	(0.808)	(0.980)
Age	0.044***	0.048***	−0.059***	−0.060***	−0.060***	−0.042**
	(0.010)	(0.010)	(0.016)	(0.016)	(0.016)	(0.017)
Female	−0.008	−0.013	−0.069	−0.093*	−0.081	−0.029
	(0.060)	(0.057)	(0.046)	(0.055)	(0.055)	(0.072)
Fast food consumption	0.002	0.000	0.001	0.006	0.003	−0.001
	(0.019)	(0.018)	(0.015)	(0.015)	(0.016)	(0.019)
Time preferences	0.040	0.039	0.042*	0.050**	0.045*	0.033
	(0.026)	(0.025)	(0.023)	(0.024)	(0.024)	(0.030)
Psyc. mood		0.051***	0.028**	0.022	0.025*	0.039**
		(0.015)	(0.012)	(0.014)	(0.014)	(0.019)
Bullying		−0.138	−0.038	0.012	−0.013	−0.096
		(0.147)	(0.110)	(0.117)	(0.121)	(0.163)
Constant	−0.270	−0.475**	−0.591***	−0.433**	−0.634***	−0.954
	(0.179)	(0.210)	(0.163)	(0.208)	(0.213)	(0.924)
N	1901	1901	1901	1901	1901	1901
Controls for intransitive friend triads	NO	NO	YES	YES	YES	YES
Province FE	NO	NO	NO	YES	YES	YES
School FE	NO	NO	NO	NO	YES	YES
Class FE	NO	NO	NO	NO	NO	YES
Panel B: First stage for Obese and Female × Obese						
$\overline{\text{BMI}}$ (intransitive friend triads)	0.019**	0.020**	0.023***	0.022***	0.024***	0.023**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Female × $\overline{\text{BMI}}$	0.026***	0.026***	0.025***	0.024***	0.023***	0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

our self-reported data on weight and height are unlikely to be affected by intentional or systematic measurement errors by respondents. Therefore, the self-reported data that we use are considered valid as measured data, although unintentional measurement errors cannot be completely ruled out.

The main findings of this paper can be summarized as follows: (1) Obesity is associated with decreased academic performance in several educational outcomes. Specifically, it negatively affects general scores for girls and cognitive abilities, measured by CRT scores, for both boys and girls. It also has a negative effect on the probability that girls achieve an A grade in mathematics, while the effect for boys is positive. (2) Class-fixed effects appear to be a key factor in the negative association between obesity and general scores among girls, as controlling for these effects eliminates the observed impact. Given that general scores are assigned by teachers, and class-fixed effects either do not significantly influence other educational outcomes or account for a smaller portion of the effect, we suggest that teacher bias may contribute to the negative relationship between obesity and girls' general scores. However, to establish teacher discrimination as a causal mechanism, it would be necessary to include teacher fixed effects in the model, data that, unfortunately, are not available in our study. (3) There is no evidence to suggest that bullying explains the relationship between obesity and any of the outcomes considered. (4) Although the evidence is not conclusive, there are indications that expectations of potential discrimination in the labor market may play a role in the negative impact of obesity on the development of human capital. This effect may be particularly relevant in the service sector and in the creation of online 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 results. 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, 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 to obese children could serve as effective policy complements.

CRediT authorship contribution statement

Raquel Carrasco: Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Diego González-González:** Methodology, Formal analysis, Data curation, Conceptualization.

Appendix

See Fig. A.1 and Tables A.1–A.6.

Data availability

Data will be made available on request.

Table A.5
2SLS estimates for As in mathematics.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two Stage Least Squares						
Obese	0.184	−0.111	−0.523	0.151	−0.103	0.701
	(0.880)	(0.863)	(0.866)	(1.080)	(1.081)	(1.423)
Female × Obese	−0.462	−0.141	0.223	−0.297	−0.106	−0.765
	(1.142)	(1.124)	(1.151)	(1.309)	(1.308)	(1.537)
Age	−0.069***	−0.059***	−0.124***	−0.124***	−0.123***	−0.114***
	(0.012)	(0.013)	(0.022)	(0.022)	(0.022)	(0.023)
Female	0.002	−0.016	−0.052	−0.007	−0.024	0.043
	(0.074)	(0.074)	(0.076)	(0.091)	(0.091)	(0.116)
Fast food consumption	0.056**	0.052**	0.047*	0.036	0.040	0.038
	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.028)
Time preferences	0.075**	0.071**	0.070*	0.055	0.060	0.027
	(0.033)	(0.033)	(0.038)	(0.039)	(0.040)	(0.045)
Psyc. mood		0.109***	0.092***	0.104***	0.099***	0.117***
		(0.019)	(0.020)	(0.023)	(0.023)	(0.028)
Bullying		−0.002	0.059	−0.031	0.007	−0.116
		(0.148)	(0.160)	(0.185)	(0.183)	(0.234)
Constant	1.198***	0.762***	0.492*	0.392	0.432	0.783
	(0.207)	(0.258)	(0.269)	(0.341)	(0.342)	(1.286)
N	1901	1901	1901	1901	1901	1901
Controls for intransitive friend triads	NO	NO	YES	YES	YES	YES
Province FE	NO	NO	NO	YES	YES	YES
School FE	NO	NO	NO	NO	YES	YES
Class FE	NO	NO	NO	NO	NO	YES
Panel B: First stage for Obese and Female × Obese						
$\overline{\text{BMI}}$ (intransitive friend triads)	0.019**	0.020**	0.023***	0.022***	0.024***	0.023**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Female × $\overline{\text{BMI}}$	0.026***	0.026***	0.025***	0.024***	0.023***	0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

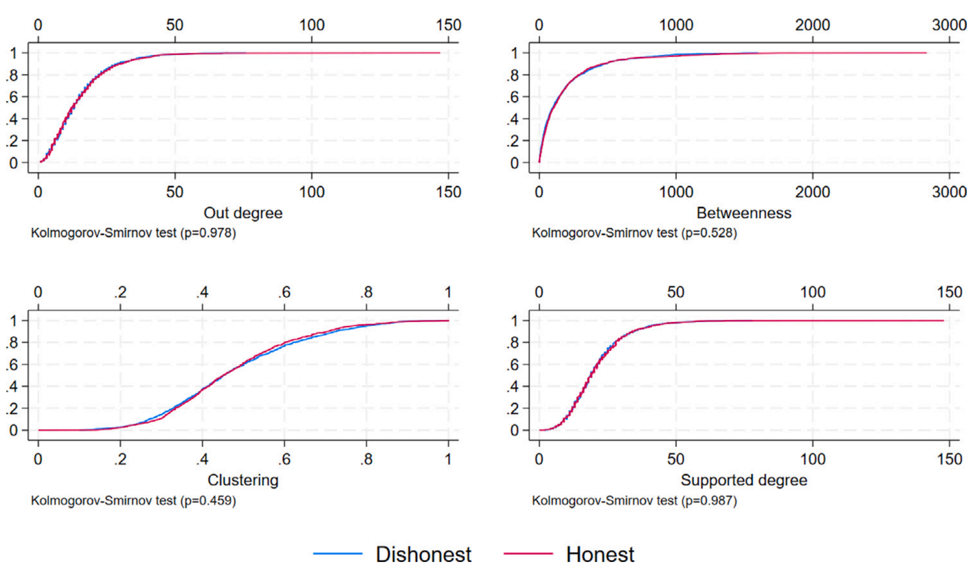

Fig. A.1. Cumulative distributions of different centrality measures in friendship networks by honesty.

Table A.6
2SLS estimates for As in English.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two Stage Least Squares						
Obese	−0.718	−0.981	−1.667	−0.805	−0.903	−0.819
	(0.877)	(0.903)	(1.035)	(1.106)	(1.132)	(1.417)
Female × Obese	0.068	0.357	1.009	0.250	0.290	0.194
	(1.142)	(1.178)	(1.358)	(1.359)	(1.384)	(1.531)
Age	−0.064***	−0.056***	−0.148***	−0.146***	−0.146***	−0.136***
	(0.011)	(0.013)	(0.026)	(0.021)	(0.022)	(0.021)
Female	0.068	0.050	−0.009	0.051	0.045	0.056
	(0.073)	(0.077)	(0.089)	(0.093)	(0.095)	(0.115)
Fast food consumption	0.113***	0.110***	0.106***	0.095***	0.096***	0.106***
	(0.024)	(0.025)	(0.029)	(0.026)	(0.026)	(0.029)
Time preferences	0.057	0.053	0.075	0.056	0.061	0.056
	(0.034)	(0.035)	(0.046)	(0.041)	(0.042)	(0.047)
Psyc. mood		0.087***	0.070***	0.084***	0.083***	0.080***
		(0.020)	(0.025)	(0.024)	(0.024)	(0.028)
Bullying		0.136	0.294	0.172	0.185	0.158
		(0.175)	(0.225)	(0.202)	(0.207)	(0.237)
Constant	1.093***	0.748***	0.800**	0.422	0.322	2.967**
	(0.203)	(0.269)	(0.314)	(0.351)	(0.366)	(1.431)
N	1901	1901	1901	1901	1901	1901
Controls for intransitive friend triads	NO	NO	YES	YES	YES	YES
Province FE	NO	NO	NO	YES	YES	YES
School FE	NO	NO	NO	NO	YES	YES
Class FE	NO	NO	NO	NO	NO	YES
Panel B: First stage for Obese and Female × Obese						
$\overline{\text{BMI}}$ (intransitive friend triads)	0.019**	0.020**	0.023***	0.022***	0.024***	0.023**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Female × $\overline{\text{BMI}}$	0.026***	0.026***	0.025***	0.024***	0.023***	0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)

Notes: Standard errors are adjusted for primary sampling units clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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