Food Coma is Real: The Effect of Digestive Fatigue on Adolescents' Cognitive Performance

Justine Hervé* Subha Mani† Jere Behrman‡ Ramanan Laxminarayan§
Arindam Nandi¶

September 11, 2023

Abstract

Food coma, often referred to as postprandial somnolence, is a commonly cited reason for experiencing reduced alertness during mid-afternoon worldwide. This is the first study to examine the impact of food coma on cognitive performance. By exploiting exogenous variation in the time of tests, thereby creating quasi-random variation in the time interval between test-taking and an individual's last meal, we uncover the causal relationship between food coma and cognitive performance. Using rich data on $\sim$ 4,000 Indian adolescents, we find that testing immediately after a meal reduces adolescents' scores on English, native languages, math, and Raven's tests by 9, 8, 7, and 17 percent, respectively, compared to students who took the tests more than an hour after a meal. We further find that the negative effect of postprandial somnolence on cognition works through an increased feeling of fatigue. Moreover, this effect becomes more pronounced when dealing with more challenging questions on a test.

Keywords: Post-meal Fatigue, Cognitive skills, Low-stakes tests, India, Adolescents
JEL codes: I12, I18, I21, J24

*School of Business, Stevens Institute of Technology. Email (Corresponding author): jherve@stevens.edu.

†Department of Economics, Fordham University. Email: smani@fordham.edu.

‡Department of Economics and the Population Studies Center, University of Pennsylvania. Email: jbehrman@econ.upenn.edu.

§One Health Trust and Princeton University. Email: ramanan@onehealthtrust.org.

¶The Population Council. Email: anandi@populationcouncil.org.

‖This study acknowledges funding support from 3ie (International Initiatives for Impact Evaluation), UPIASI (University of Pennsylvania Institute for the Advanced Study of India), and the India Research Engagement Fund (IREF) at the University of Pennsylvania. We thank Pranava Kadiyala, Aanchal Bagga, and Abhik Banerji for excellent research assistance. The findings contained within are those of the authors and do not reflect policies of the funding organizations. All remaining errors are our own.

1 Introduction

Standardized tests on language, math, and analytical reasoning have become indispensable for assessing children's academic performance worldwide, especially in low- and middle-income countries where reliable data on children's learning levels often remain unavailable (ASER, 2018). The credibility and interpretation of these tests rely on the assumption that testing conditions, test content, and scoring procedures are identical for all test takers. Because of these features, standardized tests are globally trusted to give unbiased representations of children's cognitive skills and are used to evaluate the effectiveness of educational and social-policy programs.

However, research has shown that factors beyond cognitive skills often impact student performance on cognitive tests. Test-taking conditions, such as incentives (Behrman et al., 2015; Bettinger, 2012; Jalava et al., 2015; Gneezy et al., 2019), environmental factors including contemporaneous temperature (Zhang et al., 2021) and pollution (Ebenstein et al., 2016), and the time of the day (Goldstein et al., 2007; Dills and Hernandez-Julian, 2008; Sievertsen et al., 2016; Pope, 2016; Gaggero and Tommasi, 2023) are found to impact performance on tests. Time-of-day effects documented in the literature capture the impact of variations in alertness experienced throughout the day due to changes in testing conditions (e.g., testing after a break) or natural fluctuations in one's circadian rhythm. However, no study has yet formalized the effect of another temporary source of sleepiness commonly experienced worldwide, namely, digestive fatigue or food coma.

Food coma is a feeling of tiredness that often occurs after consuming a meal, commonly referred to as the "postprandial dip". In the medical literature, the term "postprandial" refers to phenomena happening after eating and evidence suggests that the postprandial period induces hormonal peaks around thirty minutes to an hour after a meal (Alleman Jr and Bloomer, 2011; Takahashi et al., 2018). Food coma is a commonly cited reason for experiencing reduced alertness during mid-afternoon worldwide. Yet, the scientific evidence on the cognitive impact of the postprandial dip is limited (Roberts et al., 2001; Monk, 2005; Reyner et al., 2012; Chaturvedi et al., 2021). This is mostly because assessing the impact of food coma on cognitive performance is quite challenging. First, in high-stake settings, the time of the test is known to the individual ahead of time, which can result in behavioral responses such as, drinking caffeine, or eating a small meal to minimize the influence of food coma on test scores or job performance. Thus, it is only when the time-of-test is truly unknown that the estimated causal impact of food coma on standardized tests are not conflated by individual behavioral responses. Second, there is globally no data set that includes information on meal timing and test scores, making it impossible to examine the impact of food coma on performance. Third, most administrative data sets that have been used to explore the effect of test timing do not collect any information on subjective feelings of tiredness, and, as a result, there is no data and empirical evidence on the key underlying mechanism, namely, fatigue, which is cited in the literature (Roberts et al., 2001; Monk, 2005; Reyner et al., 2012; Chaturvedi et al., 2021).

In this study, we overcome all these limitations by using exogenous variation in the timing of the tests and hence, by extension, plausibly exogenous variation in the temporal distance between the last meals and the time of tests, to examine the causal impact of postprandial testing on cognitive performance. We collected data on testing conditions and test scores for approximately 4,000 adolescents and young adults between the ages of 12 and 22 years from two rural districts in Maharashtra and Andhra Pradesh in India. The time at which interviewers visit households is plausibly exogenous, that is, determined by the number of enumerators and field plan for the day and does not use any pre-existing information on child and household characteristics such as education and income. We only use data from adolescents and young adults who could be reached at the time of the household's "first visit", as "second visits" to the household could be correlated with unobserved household characteristics that also determine parental investments in children's cognitive attainments. At the times of the first visit to the household, respondents could not have known in advance when they would be tested. This provides us with the necessary exogenous variation in the timing of tests with respect to individual and household characteristics, which constitutes the basis of our identification strategy. To track testing conditions, we collected time use information on subjects' activities around the times of the test, among which we recorded the times of the tests, the times at which respondents woke up, and the times at which they had their last meals. Based on medical research that has identified postprandial hormonal peaks thirty to sixty minutes after meals (Alleman Jr and Bloomer, 2011; Takahashi et al., 2018), we then compare the results of children who ate their meal less than an hour or an hour before the tests to those of children who took the tests more than an hour after their last meal.[1] We assess the causal effect of postprandial dip/food coma on adolescents' performances on a wide range of measures including tests of reading, math, oral comprehension, and fluid intelligence that capture multidimensional learning.

We find that postprandial/digestive somnolence considerably decreases students' measured cognitive skills. Students who took tests less than an hour after their last meals perform significantly worse than students who tested more than an hour after their last food intakes. For example, their scores on reading tests in native and English languages, math tests, and fluid intelligence tests are 0.31 (∼9 percent), 0.25 (∼ 8 percent), 0.25 (∼ 7 percent) and 0.47 standard deviations (∼ 17 percent) lower than those of students who took the tests more than an hour after meals. We also find that the effect of postprandial testing varies by the levels of difficulty of the tests. Specifically, the negative effects of postprandial testing on test performances are stronger when test questions are more challenging. Testing right after meals decreases measured reading proficiency by 19 percent for paragraphs, 8 percent for sentences, and 4 percent for individual words. This pattern is similarly observed in math question performance. Finally, we are able to show that the negative effects of food coma on cognition mainly operate through increases in fatigue right after meals, which depletes individuals' cognitive resources. Specifically, our findings imply

[1] Also see Figure 1 to further see the motivation for the treatment variable definition

that testing less than an hour after meals increases students' level of reported fatigue[2] by 0.38 standard deviations compared to students who took tests more than an hour after their last meals (i.e. control group). This finding aligns with existing evidence from the medical literature that shows that sleepiness inhibits our cognitive capacities to solve problems (Roberts et al., 2001; Alhola and Polo-Kantola, 2007; Reyner et al., 2012; Lo et al., 2016).

This paper makes several contributions to the economics literature. First, this study broadly contributes to the nascent and relatively scarce literature on the causes of fatigue and its economic effects. Studies looking at the consequences of fatigue find a negative impact on human capital production (Jagnani, 2022), decision-making (Mullette-Gillman et al., 2015), productivity and job performance (Hafner et al., 2017; Bessone et al., 2021). On the causes of fatigue, a few papers identify sleep deprivation (Hafner et al., 2017; Bessone et al., 2021; Rao et al., 2021), long working hours (Park et al., 2001; Beckers et al., 2004; Nagashima et al., 2007) and high workloads (Baulk et al., 2007; Grech et al., 2009) as factors contributing to cognitive exhaustion. Yet, no study has so far considered the postprandial dip as a source of fatigue that can significantly alter individuals' cognitive functioning. Considering this, we broaden the existing body of literature on the cognitive repercussions of fatigue (Ebenstein et al., 2016). By using unique data on students' performance and time distances from meals as a novel outcome, we are able to investigate the effect of postprandial dip on test scores, which, to our knowledge has never been explored before. Not only are we able to look at these associations, but the randomized timing of the tests allows us to make causal claims.

Second, by showing that the effects of food coma worsen with the difficulty of the tasks, our finding also aligns with the literature on attention and cognitive load, which highlight the negative effects of cognitive burden on learning (Sweller, 1988). In our context, the difficulty of tasks make the negative effects of postprandial fatigue more salient by increasing respondents' cognitive loads. In other words, the postprandial dip might deplete

[2] Respondent's self-rated measure of fatigue at the time of test, ranges from 1 to 5 32

individuals from their cognitive resources, while sleep has been shown to be needed for their regeneration (Schilbach et al., 2016; Kamstra et al., 2000; Jin and Ziebarth, 2020; Holbein et al., 2019; Wagner et al., 2012; Gibson and Shrader, 2018; Rao et al., 2021).

Third, our study specifically contributes to the literature on naps and productivity (Lovato and Lack, 2010; Bessone et al., 2021) by explaining why naps restore cognition: they repair the intellectual capacities that were partially exhausted in the digestive period. Specifically, our finding helps reconcile Bessone et al. (2021)'s surprising result that naps are more efficient than increased night sleep at improving cognition and productivity. We provide a possible explanation for their result: Daytime naps are important because they restore the cognitive resources depleted by the postprandial dip.

Finally, we contribute to the literature on the determinants of students' performance on tests. Specifically, we engage with the debate stirred by Wise and DeMars (2005), Finn (2015) and Gneezy et al. (2019), which suggests that students' scores on low-stakes tests might not always reflect their true skills. Our contribution lies in identifying postprandial fatigue as another source of underestimation of true skill gaps across cultures on low-stakes tests. Specifically, we find that the SES gaps in student performances noted in the literature might be much worse as food coma reduces high SES children's performance more than low SES children due to differences in meal compositions (Fernald et al., 2011; Schady et al., 2015; Hervé et al., 2022).

The rest of the paper is organized as follows. Section 2 offers some background on the causes and consequences of the postprandial dip. Section 3 describes our data, the sampling strategy, and the variables used in the analysis. Section 4 outlines our research methodology, reports our main results on the effects of post-meal testing on test scores, and explores heterogeneity in outcomes and possible mechanisms. Section 5 presents robustness checks and concluding remarks follow in Section 6.

2 What is food coma?

This section provides a brief overview on the causes and consequences of the post-meal dip. The medical literature has investigated the physiological causes of the post-meal dip, however the debate about the sources of this phenomenon is still ongoing. In addition, evidence on the economic and psychological consequences of this phenomenon is still quite scarce, most likely because the study of this subject has so far received little attention from psychologists and economists.

For a long time, a commonly accepted explanation for post-meal sleepiness was that blood flows are redistributed away from the brain after meals, with research showing that this phenomenon worsens in the absence of breakfast (Ishizeki et al., 2019). This hypothesis has however been recently discarded in favor of new evidence suggesting that post-meal fatigue might instead be caused by hormonal changes (release of melatonin) and activation of the sleep centers in the brain. Indeed, it appears that some nerve pathways implicated in the digestion are similar to those implicated in sleep, such that when these neural routes are activated after meals, individuals might start feeling drowsy (Bazar et al., 2004; Kim and Lee, 2009a). Along with this hypothesis, an alternative theory is that food coma is part of humans' bi-circadian rhythm, in which individuals experience sleepy phase in the early afternoon in addition to the nighttime sleeping period (Reyner et al., 2012; Slama et al., 2015; Shukla and Basheer, 2016). Yet, other important factors mentioned in the literature are meal compositions and meal sizes - research shows that the detrimental effects of post-lunch dips on cognition are higher with larger meals (Reyner et al., 2012; Murphy et al., 2016; Hengist et al., 2020), and foods with high fat, high sugar or high carbohydrate contents (Kim and Lee, 2009a; Vlahoyiannis et al., 2021; Lehrskov et al., 2018). Because meal compositions seem important in the context of our sample, we further address them in the "Results" section of the paper. Finally, there is very little to no evidence on the length of food comas, but Ishizeki et al. (2019) found a decrease in blood flows to the brain up to an hour after meals, while other studies have reported that effects have been observed up to four hours after meals (Hengist et al., 2020).

Yet, little is known about the cognitive and economic consequences of postprandial somnolence, mostly because the postprandial dip has so far mostly been studied in the medical field. The medical literature has shown that meals and particularly lunch are associated with lower cognitive vigilance (Smith and Miles, 1986), higher measures of subjective and objective measures of daytime drowsiness that cannot only be attributed to circadian rhythm (Wells et al., 1998), and decreased individuals' driving abilities (Reyner et al. (2012)). Complementarily, evidence suggests that afternoon naps may help prevent food coma and restore workers' productivity (Hayashi et al., 1999; Hayashi et al., 2005; Slama et al., 2015 ; Bessone et al., 2021). As can be seen from above, however, no study has yet formally investigated the effects of the post-meal dips on cognitive performances. By addressing this gap, the present study makes a valuable addition to both educational research and, by extension, labor economics since students' performances on standardized tests are an important predictor of success in the labor market.

3 Data

3.1 Sample description

This paper mainly uses the endline household and individual surveys collected by the research team as part of a larger project whose aim is to examine the impact of Magic Bus Foundation's community-led sports-based curriculum on education, gender attitudes, socioemotional outcomes, and health in India.[3] As part of this larger project, we collected three rounds of data – during August-November 2015, we collected baseline data on children between the ages of 8 and 14 years residing across 158 rural villages across two districts in Andhra Pradesh and Maharashtra, India (see Hervé et al. (2022) for detailed discussion on sampling). We conducted the first follow-up survey during March-May 2018 and the endline survey, which targeted a random subset of the baseline respondents, between March-June

[3] This experiment is registered with the AEA registry and has a trial id of AEARCTR-0000518.

2022.

In this paper, we use the endline individual-level surveys administered to adolescents and young adults who were initially between the ages of 8 and 14 years in 2015. These surveys provide information on the respondents' ages, sex, school enrollment status, completed grades of schooling, and most importantly, measures of cognitive skills along with detailed information on the timing of these tests. Specifically, respondents' math and language skills were assessed using the Annual Status of Education Report (ASER, 2018) testing tools. In Asia and Africa, the ASER tests are standard tools to evaluate cognitive/learning skills among children/adolescents (Banerji et al., 2013; Shah and Steinberg, 2017; Muralidharan et al., 2019). In the math tests, we tested respondents' abilities to divide, subtract, and recognize numbers. For language aptitude, individuals were tested on their abilities to read in their native languages (e.g., Urdu/Telugu or Marathi) and English. For each language, we assessed the youths' abilities to read a paragraph, read a sentence, recognize words, and recognize letters. Additionally, we also used Raven's progression matrices to measure students' analytical skills (Dasgupta et al., 2022). Raven's tests are used to capture individuals' fluid intelligence, in contrast to the ASER reading tests which aim to measure students' crystallized intelligence. Finally, we also implemented a unique set of oral comprehension tests to assess respondents' comprehension of a short story, in which respondents were read a short passage and were then asked three questions about the narrative. This is important as a lot of tasks in low-income countries may not require reading comprehension and instead rely on oral comprehension.

In the individual-level endline surveys, we also collected data on respondents' time use around the time of the tests. We recorded the times at which adolescents started and ended each test. Since the times at which households are visited were purely determined by field logistics such as the number of available interviewers, field plans for the day, and since the enumerators had no other data on the household accessible to them, the times of tests are as good as random. This feature of the data is particularly important since we exploit random variation in test timing to identify the effect of post-meal testing on test scores.

In the time-use section, we also gathered information about respondents' activities before taking the tests: we asked them at what time they woke up the days of the test, and we also recorded a self-reported measure of fatigue that to our knowledge had never been collected before. Most importantly, for the purpose of this analysis, we asked subjects at what time they had their last meal. Another important aspect of our study is that we gathered data on respondents' performances on tests and testing conditions via household surveys instead of school-based surveys as this allows us to alleviate selection concerns stemming from children/adolescents' absenteeism and non-enrolment, which are important sources of sample selection in developing countries (Schady et al., 2015; Tamiru et al., 2016).

We then combine these endline data with information available in the baseline survey in 2015 to obtain information on household-level background characteristics.[4] The baseline survey gathered data on household demographics such as ages, gender, education levels and work status of household members, as well as socio-economic status, assets, and participation in social interventions.[5]

3.2 Variable definitions

Time of last meal: We collected data on time of last meal, which are recorded as a categorical variable ranging from 1 to 5: (1) if respondents ate less than an hour before the tests, (2) if respondents ate one-to-two hours before the tests, (3) if respondents ate two-to-three hours prior to the tests, (4) if respondents ate three-to-four hours before the tests and (5) if respondents ate more than four hours before. Using this information, we define the "treatment" dummy that takes a value 1 if respondents were tested less than or an hour after their last meals, and 0 if they took the tests more than an hour after their last meals. A complete description of these variables is available in Panel A, Table 1.

Cognitive skills: We create five outcome variables to capture the respondents' perfor-

[4] 20% of the sample were between 10 and 13 years old, 47% were between 14 and 17 years old, and 32% belonged to the 18-22 age range.

[5] These data were not collected in endline which is why we use the baseline information instead. The use of the baseline data also avoids possible biases if these characteristics were affected by the intervention.

mance in five tests. The cognitive tests include a reading test in native language, a reading test in English, a math test, a Raven's test, and a test of oral comprehension. Reading abilities are evaluated through adolescents' scores on reading tests in their native language and English. The scores in these tests range from 0 to 4: (0) if respondents cannot read letters, (1) if they can at best read letters, (2) if they can read words, (3) if they can read sentences, and (4) if they can read a paragraph. Similarly, scores on the math test range from 0 to 4, taking the value 0 if a respondent cannot recognize numbers, (1) if they can read numbers 1-9, (2) if they can read numbers 11-99, (3) if they can subtract and (4) if they can perform division. The Raven's score records the number of correct answers obtained on a 10-item Raven's inventory. Finally, the oral comprehension score is based on adolescents' answers to three questions following the reading of a short paragraph by the interviewers. This score ranges from 0 to 3: (0) if the respondents answered all questions wrongly, (1) if they gave at best one correct answer, (2) if they answered two questions out of three correctly, and (3) if all their answers were correct. A complete description of these variables is available in Panel B, Table 1.

Testing conditions: We create a set of variables recording information about respondents' time uses before they took the tests. We first create a variable recording the times of the tests. Another continuous variable records the times at which the respondents woke up the days of the tests. Finally, we create a continuous variable that captures a respondents' self-reported levels of fatigue at the times of the tests, by recording the answer to the following statement "I feel tired. What will you say": (1) strongly agree, (2) Agree, (3) Disagree and (4) Strongly disagree. A complete description of these variables is available in Panel C, Table 1.

Background characteristics: We present a full list of household and individual-level characteristics in Panel D, Table 1. All these measures are obtained from the 2015 survey, that is, the baseline survey, and hence must, by construction, be uncorrelated with the timings of tests, which are quasi-random. At the individual level, we control for respondents' ages, gender, enrollment status, completed grades of schooling, work status, parents' ages, and educational levels. At the household level, we measure socioeconomic status through the terciles of an asset index that measures household wealth, using the principal component analysis method utilized by Pollitt et al. (1993) and Filmer and Pritchett (2001). We also include variables recording the household sizes, the co-residence of grandparents, household resources (availability of drinking water, lighting, cooking fuel and toilets), scheduled castes or tribes' membership, religious affiliations, and participation in social programs.

3.3 Summary Statistics

We report summary statistics on all outcome variables and baseline demographic variables in Table 2. In Table 3, we further check if the baseline household and individual background characteristics are similar between the treatment group (those who were tested within an hour from their last meal) and the control group (those who were tested more than an hour after their last meal). Out of 19 variables examined in Table 3, most differences between the treatment and control groups are not significantly different at the 1 percent level or 5 percent level, except for age and the scheduled-caste dummy. Since statistical significance increases in sample size and the number of outcomes tested, we also present normalized differences in demographic characteristics in Column (4), and find that almost all differences between the treatment and control group are small and well under the 0.25 threshold suggested by Imbens and Rubin (2015), except age.[6] Once we account for Type I error in the reported differences in Column 3 of Table 3, only the difference in age between the treatment and the control group remains statistically significant. To address this baseline difference in age across control and treatment groups, our preferred estimates include a continuous measure of age as well as age-group fixed effects.

In Figure 1 below, we report standardized[7] average reading scores in native languages, reading scores in English, oral comprehension scores, Raven's test scores, and math scores by time since last meal. These figures show that there exists a steep gradient in students'

[6]Individuals in the treatment group are on average six months younger than those in the control group.
[7]Scores are standardized with respect to the control group means.

performances on cognitive tests with respect to the times of their last meals. The further away from meals, the better students perform on all types of tests. Most importantly, youth who took tests less than an hour after meals scored significantly lower in all cognitive domains than students who took tests more than an hour after their last meals.

4 Results

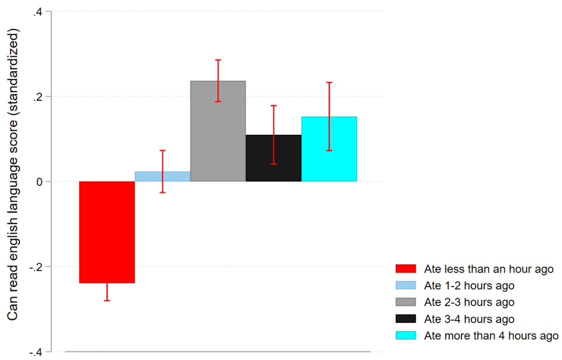
4.1 Empirical specification

We estimate the following linear regression model using OLS to estimate the effects of post-meal testing on respondents' test scores:

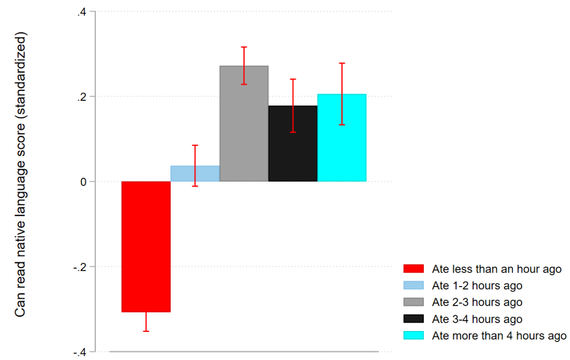
$$Score_{i,hh} = \alpha + \beta Treatment_{i,hh} + \gamma' X_{i,hh} + \phi_v + \epsilon_{i,hh} \tag{1}$$

where $Score_{i,hh}$ is a vector of cognitive skills defined in Panel A of Table 1 measured for respondent i in household hh. $Treatment_{i,hh}$ is a binary variable that takes the value 1 if individual i in household hh had a meal an hour or less before testing, 0 if this individual ate more than an hour before the test. β captures the causal effect of food coma on cognitive skills. Because all outcome indices are standardized with respect to the mean and standard deviation of the control group, the β coefficients can be interpreted in terms of standard deviation units of the control group. X contains the full set of exogenous covariates described in panel D of Table 1. Finally, ϕ_v are village fixed effects that control for village-level factors such as the quality of local schools or local climate shocks such as rainfall or temperature patterns.[8]

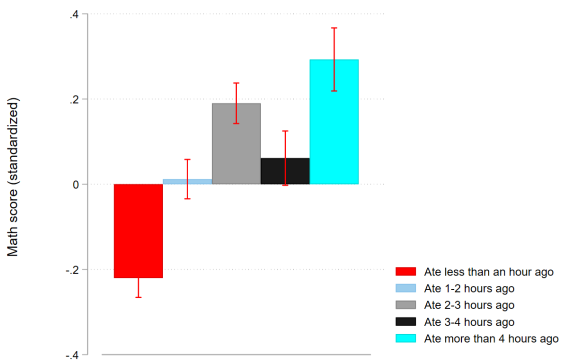
[8] We also add age-group fixed effects to mitigate the concern that differences in ages between students in the treatment group and those in the control group could explain our observed differences in cognitive skills between these two groups.



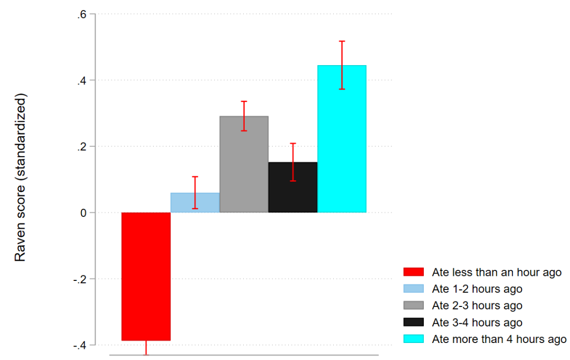
(a) Can read in English



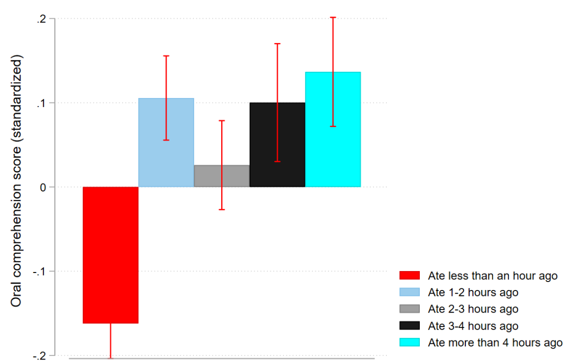
(b) Can read in Native language



(c) Math score



(d) Raven's test score



(e) Oral comprehension score

Figure 1: Standardized cognitive indices by time distances from last meals

4.2 Impact on Cognitive Outcomes

Table 4 presents the main findings of the paper, that is, the causal impact of postprandial testing on cognitive achievement. Across all measures of cognitive skills, we find that testing less than or an hour after a meal decreases respondents' scores in reading in native language, reading in English, math, fluid intelligence and oral comprehension by 0.31, 0.24, 0.25, 0.47, 0.14 standard deviations, respectively, compared to the control group who were tested more than an hour after their last meals. The effect sizes are considerable - put in percentage terms, they suggest that individuals who tested less than an hour after meals scored 9 percent lower in reading in native language, 8 percent lower in reading in English, 7 percent lower in mathematics, 16 percent lower in fluid intelligence, and 5 percent lower in oral comprehension compared to the control group. We note that our findings maintain their statistical significance when considering Type I error.[9] Employing the methodology proposed by Benjamini and executed by Anderson, we calculate sharpened two-stage q-values, as presented in Table 4. These sharpened two-stage q-values suggest that the observed impacts remain statistically significant at the 1 percent level.

Overall, these results suggest that testing less than an hour after meals considerably damages students' measured cognitive abilities in all cognitive domains of crystallized and fluid intelligence. While this fact had never been formally identified before, it aligns with research demonstrating the beneficial effects of naps on cognition and productivity (Lovato and Lack, 2010; Bessone et al., 2021). Our identification of the negative effect of the postprandial dip on cognition might also explain why studies such as Bessone et al. (2021) find that naps have much larger positive effects on cognition and productivity compared to increased nighttime sleep.

[9] Type I error increases with the number of outcomes tested and can lead to an over-rejection on the null hypothesis.

4.3 Mechanism

We explore the mechanism through which post-meal testing could impact cognitive skills. We use respondents' self-rated measures of fatigue to assess whether the negative effect of post-meal testing works through increased fatigue after meals. In Table 5, we present the causal impact of the postprandial period on reported fatigue and find that asking respondents about their level of fatigue less than or an hour after their last meals increases levels of reported fatigue by 0.39 standard deviations compared to the control group who were asked and then tested more than an hour after their last meals. This result aligns with the medical literature identifying a postprandial dip manifesting in increased sensations of drowsiness and somnolence after lunchtime (Roberts et al., 2001; Monk, 2005; Reyner et al., 2012; Chaturvedi et al., 2021), and with research finding restorative power of naps on cognition (Lovato and Lack, 2010; Bessone et al., 2021).

4.4 Heterogeneity analysis

In this section we explore heterogeneity in the effects of post-meal testing along several dimensions. First, we allow the effects of post-meal testing to vary by the level of difficulty in the tests' questions. The negative effects of post-meal testing on students' performance might change according to the difficulty of the tests' questions. We explore this possibility in Table 6, in which we use the individual questions involved in the creation of the reading and math indices as outcome variables. This allows us to disaggregate each cognitive domain along levels of difficulty. For instance, the reading in native language and reading in English indices are disaggregated into four binary variables recording whether a youth can (1) read a paragraph, (2) read a sentence, (3) read a word, and (4) read a letter. Each dummy takes the value 1 if respondents can perform the task, and zero otherwise. Similarly, the math index is disaggregated in four binary variables measuring whether respondents can (1) perform division, (2) perform subtraction, (3) recognize numbers from 10-99, and (4) recognize numbers from 1 to 9.

We find suggestive evidence of a "task complexity" gradient in the effects of post-meal testing on test performances. In Panel A of Table 6, taking a test less than or an hour after eating decreases the probabilities of being able to read a paragraph by 19 percent, read a sentence by 8 percent, read a word by 4 percent, while the ability to read a letter is not affected significantly by the postprandial dip. Similarly in panel B, testing less than or an hour after meals decreases the likelihood of reading a paragraph in English by 13 percent, of reading an English sentence by 14 percent, of reading a word by 6 percent and it has no significant impact on respondents' abilities to read a letter. A more nuanced but similar pattern emerges with math skills in panel C. Testing right after meals is associated with a 10 percent drop in the ability to divide, a 5 percent drop in the ability to subtract, a 8 percent drop in the ability to recognize two-digit numbers, and does not significantly affect abilities to read one-digit numbers. These findings make intuitive sense - the more difficult the test question, the more obvious the negative effects of post-meal testing on test scores. This result directly relates to the research on attention. Since more challenging questions require more thought, our findings suggest that the negative effects of postprandial testing on cognition works through a depletion of respondents' attentional resources. When tasks require more cognitive efforts or attention, the detrimental effect of postprandial fatigue becomes more salient. This interpretation corroborates the finding that naps increase cognition through a restorative effect on attention (Bessone et al., 2021). It also aligns with the literature on cognitive load showing that higher levels of cognitive loads in problem-solving tasks decrease individuals' abilities to learn (Sweller, 1988; Sweller et al., 1998; Van Merrienboer et al., 2002).

Second, considering our earlier discovery of fatigue as a mediating factor, we might expect that the impact of post-meal testing on cognitive performance may differ depending on pre-existing chronic health conditions related to fatigue and sleep. Specifically, individuals with chronic fatigue or sleeping issues might experience the post-meal dip more profoundly. Finding a more pronounced negative effect of post-meal testing for chronically fatigued/slept-deprived individuals would corroborate our earlier result that fatigue plays a pivotal role in the influence of post-meal testing on test performance. To investigate this possibility, we utilized survey questions related to health and psychological issues experienced by respondents in the two weeks leading up to the interview. Among these questions, respondents were asked about the frequency of experiencing trouble sleeping or feeling fatigued. Responses were recorded on a scale of (0) not at all, (1) several days, (2) more than half the days, and (3) nearly every day. Based on these responses, we created binary variables for chronic fatigue and chronic sleep issues, assigning a value of 1 to respondents who reported fatigue or sleep issues on more than half the days. We then re-estimate equation (1), stratifying the sample by chronic fatigue and chronic sleep issues in Tables 7 and 8, respectively. In Columns (1), (3) and (4) of Table 7, we observe a significant deterioration in reading, math, and Raven's test scores for respondents who reported chronic fatigue.[10] Estimates from Table 8 further strengthen this observation. In Columns (1) to (4), the treatment gaps in cognitive skills are 0.27, 0.21, 0.18, and 0.43 standard deviations for the non-sleep deprived respondents in panel A and almost double to 0.45, 0.46, 0.82, and 0.79 for sleep-deprived individuals in panel B. These results provide suggestive evidence that chronic fatigue or sleep issues amplify the mediating role of fatigue in the detrimental impact of the postprandial dip on cognitive skills.

Third, the effect of post-meal testing may also vary by the time of day. The postprandial dip is a phenomenon that typically occurs after consuming lunch. One of the reasons for feeling drowsier during this time is attributed to the fact that the early afternoon aligns with a particular phase in humans' circadian rhythms. However, other research suggests that the digestive process itself could also be the reason for the increased somnolence. To disentangle these two hypotheses, we assess whether the effect of post-meal testing on cognitive outcomes changes at different times of the day. We re-estimate equation (1), stratifying the sample by periods of the day. In Table 9, panels A, B and C respectively show the estimates in the samples of respondents who test in the morning, at lunchtime/afternoon and the evening. The negative effects of post-meal testing on cognitive abilities does not seem

[10]Note that the absence of statistical significance in other columns might be due to the small size of the sample in Panel B.

to change significantly with the time of day.[11] These results confirm anecdotal accounts of increased somnolence after lunch but they also show that these effects might exist at other times. Suggesting that, in addition to the circadian cycle-based explanation of the postprandial dip, other factors linked to the digestive process itself might impact cognitive alertness.

Fourth, we examine the SES differences in the impact of post-meal testing. Research has shown that the effects of the postprandial dip worsens when meals are richer in carbohydrates (Kim and Lee, 2009b; Vlahoyiannis et al., 2021; Lehrskov et al., 2018) and that the nutritional qualities of meals tend to improve with socio-economic status (SES) (Backholer et al., 2016; Michels et al., 2018; Vos et al., 2022). Given this, we test the hypothesis that a decline in meal quality exacerbates the negative effects of the postprandial dip by re-estimating equation (1), stratifying the sample by dividing it into terciles of SES. In Table 10, panels A, B and C respectively contain coefficient estimates in the samples of respondents belonging to the first, second and third SES terciles. These coefficient estimates are large and statistically significant in panels B and C but results are more muted in panel A. Most importantly, the impact of postprandial testing on test scores seems much higher in the top SES tercile than in the lowest SES tercile (p-values below 0.10 for four out of five outcomes). Specifically, there is suggestive evidence of a SES gradient in the impact of food coma on reading in native languages, reading in English, mathematics, and Raven's test scores in Columns (1) to (4) - the treatment gaps in cognitive skills are 0.10, 0.09, 0.10, and 0.29 standard deviations in SES tercile 1 and they more than double to 0.47, 0.40, 0.40, and 0.60 in SES tercile 3. By contrast, the non-monotonicity of the coefficient-estimate sizes from SES tercile 1 to SES tercile 3 in Column (5) does not allow us to conclude that there is a clear SES gradient in the effects of postprandial testing on oral comprehension. To sum up, the effects of post-meal fatigue on crystallized and fluid intelligence appear to significantly worsen as SES status improves in our sample. This result is a little surprising as it goes against the initial intuition that lower SES would be associated with worse nu-

[11]the p-values in the bottom of Table 9 suggest no differences in the effects of post-meal testing performances between the morning and the evening.

trition and thus worse postprandial effects. One explanation might be that individuals in wealthier households can afford to consume higher quantities of carbohydrates than poorer respondents.

Fifth, we examine whether post-meal testing impacts males and females differently. These results are presented in Table 11 wherein the treatment effects for the female sample are presented in Panel A and the treatment effects for the male sample are presented in Panel B, respectively. We find no evidence that the effect of post-meal testing is different for males and females.

Sixth, because adolescence is associated with specific changes in circadian rhythms (Hagenauer et al., 2009; Yip et al., 2022), the effect of the postprandial dip might change as individuals grow older. To test this hypothesis, we assess the stability of our results across age groups by reestimating equation (1), stratifying the sample by age categories in Table 12. Panel A, B and C report estimates in the early-adolescents (12-14), middle-adolescents (15-17) and young adults' samples (18-22), respectively. In Columns (1), (2) and (4), the sizes of the treatment gaps do not seem significantly different across age categories (the coefficients' differences between panels A and C are not statistically significant). By contrast, the effect of post-meal testing on Raven's test scores and oral comprehension seem to significantly decrease as we move to older age groups in Columns (3) and (5) . Overall, results in Columns (3) and (5) offer suggestive evidence that older respondents might be less sensitive to the negative effects of food coma on cognitive skills, but more research is needed to clearly corroborate these results. Confirming such a result however has important policy implications: Since adolescence is a critical time for individuals' cognitive development and the formation of human capital and social values (Kohlberg, 1976; Choudhury et al., 2006; Steinberg, 2005; Dhar et al., 2022), confirming heightened detrimental effects of food coma in that period would further support advocating for the implementation of naps in elementary and middle school.

5 Robustness tests

5.1 Placebo test

If postprandial fatigue decreases cognitive skills through higher cognitive load, we should not find a negative effect of postprandial testing on outcomes that do not involve the mobilization of attentional resources. We test this hypothesis by regressing measures of respondents' attitudes related to gender, similar to those used in Hervé et al. (2022), on the treatment dummy, using a similar specification to equation (1). We report the resulting coefficient estimates on the treatment variable in Table A1. In Columns (1) to (4), all coefficients are statistically insignificant at the 1 percent level. The absence of statistical significance aligns with the intuition that the postprandial dip should not impact non-cognitive outomes.

5.2 Alternative treatment definition

There is no consensus on the exact length of the postprandial dip but most papers in the literature mention lengths ranging from one hour to two to three hours after a meal (Stahl et al., 1983; Ishizeki et al., 2019; Nagano et al., 2022). We assess the sensitivity of our estimates to alternative definitions of the treatment variable. We allow for an extension of the postprandial time window by redefining the treatment dummy to take a value of one if respondents had meals in the two hours preceding a test, and zero if their last meals happened more than two hours before they were interviewed. These results are reported in Appendix Table A2. We find that the effect of postprandial testing on cognitive test scores remains negative and statistically significant at the one percent level, but the size of the treatment dummy goes down consistently across all measures of cognitive attainment, which is consistent with the idea that most of the effects of the postprandial dip are concentrated in the hour following meals and that the effects decrease as the times of the tests move away from the times of the meals.

5.3 Alternative sample

Because we are using endline-survey data from an experiment that could impact children's cognitive scores, we test the robustness of our results by restricting our analysis sample here to the control villages - where there are no treatment spillovers. These estimates are reported Table A3 and our main findings remain unchanged in this alternative sample.

6 Conclusions

This study identifies the causal effect of post-meal testing on cognitive performances. Using exogenous variation in the timing of tests, we show that individuals who took cognitive tests within an hour of their last meals perform worse than their counterparts who took the tests an hour or more after their last food intakes. The impact of food coma is significant and sizable and found across all measures of reading, mathematics, fluid intelligence and oral comprehension. Our analysis further suggests that these effects work through fatigue – respondents report being more tired shortly after their last meals.

Our results have three relevant and practical policy implications. First, our research findings have implications in terms of the comparability of performances on tests across settings and suggest that the post-meal dips should be considered while setting up conditions for standardized testing. If testing at 2pm versus 5pm have differential effects, then testing institutions such as PISA, GRE, SAT or TOEFL should offer comparable testing conditions to test takers and policymakers should use caution while comparing national educational systems based on such tests. Similarly, standardized tests such as OECD PISA should make sure that observed differences in test performances across countries cannot be explained by systematic differences in the times at which students typically test in different national contexts.

Second, assessing the possible effects of post-meal fatigue is important in terms of the fairness of the testing procedure - if we want to correctly compare students' skills, we should consider differences in testing conditions that might impact cognitive performance. More generally, our estimates corroborate findings that scores on low-stakes tests do not always reflect students' true skills (Wise and DeMars, 2005; Finn, 2015; Gneezy et al., 2019) and suggest that cognitive fatigue is a significant issue and can have significant impacts on low-stakes tests, with potentially important effects on high-stakes tests. More research is thus needed to better understand the causes of cognitive fatigue and to develop effective strategies for reducing its impacts.

Third, and perhaps most importantly, our results suggest that educational policies incorporating naps into students' academic schedule could improve their performance on tests. If postprandial sleepiness does indeed reduce measured cognitive skills, national educational policies should encourage and facilitate napping for students, especially given the importance of cognitive skills for human capital formation and labor market outcomes (Heckman et al., 2006). By suggesting naps as a potentially effective intervention for young individuals, our paper also indirectly contributes to the research on youth development (Walker et al., 2007; Engle et al., 2011; Mani et al., 2012; Boyden and Dercon, 2012; Sutter et al., 2019).

References

Alhola, P., & Polo-Kantola, P. (2007). Sleep deprivation: Impact on cognitive performance. *Neuropsychiatric disease and treatment*, *3*(5), 553–567.

Alleman Jr, R. J., & Bloomer, R. J. (2011). Hormonal response to lipid and carbohydrate meals during the acute postprandial period. *Journal of the International Society of Sports Nutrition*, *8*(1), 19.

ASER. (2018). Annual Status of Education Report. *New Delhi: ASER Center*.

Backholer, K., Spencer, E., Gearon, E., Magliano, D. J., McNaughton, S. A., Shaw, J. E., & Peeters, A. (2016). The association between socio-economic position and diet quality in australian adults. *Public health nutrition*, *19*(3), 477–485.

Banerji, R., Bhattacharjea, S., & Wadhwa, W. (2013). The annual status of education report (aser). *Research in Comparative and International Education*, *8*(3), 387–396.

Baulk, S. D., Kandelaars, K. J., Lamond, N., Roach, G. D., Dawson, D., & Fletcher, A. (2007). Does variation in workload affect fatigue in a regular 12-hour shift system? *Sleep and Biological Rhythms*, *5*(1), 74–77.

Bazar, K. A., Yun, A. J., & Lee, P. Y. (2004). Debunking a myth: Neurohormonal and vagal modulation of sleep centers, not redistribution of blood flow, may account for postprandial somnolence. *Medical hypotheses*, *63*(5), 778–782.

Beckers, D. G. J., van der Linden, D., Smulders, P. G., Kompier, M. A. J., van Veldhoven, M. J. P. M., & van Yperen, N. W. (2004). Working Overtime Hours: Relations with Fatigue, Work Motivation, and the Quality of Work. *Journal of Occupational and Environmental Medicine*, *46*(12), 1282–1289.

Behrman, J. R., Parker, S. W., Todd, P. E., & Wolpin, K. I. (2015). Aligning learning incentives of students and teachers: Results from a social experiment in mexican high schools. *Journal of Political Economy*, *123*(2), 325–364.

Bessone, P., Rao, G., Schilbach, F., Schofield, H., & Toma, M. (2021). The economic consequences of increasing sleep among the urban poor. *The Quarterly Journal of Economics*, *136*(3), 1887–1941.

Bettinger, E. P. (2012). Paying to learn: The effect of financial incentives on elementary school test scores. *Review of Economics and Statistics*, *94*(3), 686–698.

Boyden, J., & Dercon, S. (2012). *Child development and economic development: Lessons and future challenges*. Young Lives Oxford.

Chaturvedi, A., Guru, A., Kumar, N., Lin, L. Y., Wei, D. Y., Sheng, L. K., & Yee, L. H. (2021). Postprandial Somnolence and its awareness among the Medical Undergraduate Students: A crosssectional study. *Bangladesh Journal of Medical Science*, *20*(4), 826–832.

Choudhury, S., Blakemore, S.-J., & Charman, T. (2006). Social cognitive development during adolescence. *Social cognitive and affective neuroscience*, *1*(3), 165.

Dasgupta, U., Mani, S., Sharma, S., & Singhal, S. (2022). Effects of Peers and Rank on Cognition, Preferences, and Personality. *The Review of Economics and Statistics*, *104*(3), 587–601.

Dhar, D., Jain, T., & Jayachandran, S. (2022). Reshaping adolescents' gender attitudes: Evidence from a school-based experiment in India. *American economic review*, *112*(3), 899–927.

Dills, A. K., & Hernandez-Julian, R. (2008). Course scheduling and academic performance. *Economics of Education Review*, *27*(6), 646–654.

Ebenstein, A., Lavy, V., & Roth, S. (2016). The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, *8*(4), 36–65.

Engle, P. L., Fernald, L. C., Alderman, H., Behrman, J., O'Gara, C., Yousafzai, A., De Mello, M. C., Hidrobo, M., Ulkuer, N., & Ertem, I. (2011). Strategies for reducing inequalities and improving developmental outcomes for young children in low-income and middle-income countries. *The lancet*, *378*(9799), 1339–1353.

Fernald, L. C., Weber, A., Galasso, E., & Ratsifandrihamanana, L. (2011). Socioeconomic gradients and child development in a very low income population: Evidence from madagascar. *Developmental science*, *14*(4), 832–847.

Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data—or tears: An application to educational enrollments in states of India. *Demography*, *38*(1), 115–132.

Finn, B. (2015). Measuring motivation in low-stakes assessments. *ETS Research Report Series*, *2015*(2), 1–17.

Gaggero, A., & Tommasi, D. (2023). Time of Day and High-Stake Cognitive Assessments. *The Economic Journal*, *133*(652), 1407–1429.

Gibson, M., & Shrader, J. (2018). Time use and labor productivity: The returns to sleep. *Review of Economics and Statistics*, *100*(5), 783–798.

Gneezy, U., List, J. A., Livingston, J. A., Qin, X., Sadoff, S., & Xu, Y. (2019). Measuring success in education: The role of effort on the test itself. *American Economic Review: Insights*, *1*(3), 291–308.

Goldstein, D., Hahn, C. S., Hasher, L., Wiprzycka, U. J., & Zelazo, P. D. (2007). Time of day, intellectual performance, and behavioral problems in morning versus evening type adolescents: Is there a synchrony effect? *Personality and individual Differences*, *42*(3), 431–440.

Grech, M. R., Neal, A., Yeo, G., Humphreys, M., & Smith, S. (2009). An examination of the relationship between workload and fatigue within and across consecutive days of work: Is the relationship static or dynamic? *Journal of Occupational Health Psychology*, *14*, 231–242.

Hafner, M., Stepanek, M., Taylor, J., Troxel, W. M., & van Stolk, C. (2017). Why Sleep Matters—The Economic Costs of Insufficient Sleep. *Rand Health Quarterly*, *6*(4), 11.

Hagenauer, M. H., Perryman, J. I., Lee, T. M., & Carskadon, M. A. (2009). Adolescent changes in the homeostatic and circadian regulation of sleep. *Developmental Neuroscience*, *31*(4), 276–284.

Hayashi, M., Motoyoshi, N., & Hori, T. (2005). Recuperative power of a short daytime nap with or without stage 2 sleep. *Sleep*, *28*(7), 829–836.

Hayashi, M., Watanabe, M., & Hori, T. (1999). The effects of a 20 min nap in the mid-afternoon on mood, performance and EEG activity. *Clinical Neurophysiology*, *110*(2), 272–279.

Hengist, A., Edinburgh, R. M., Davies, R. G., Walhin, J.-P., Buniam, J., James, L. J., Rogers, P. J., Gonzalez, J. T., & Betts, J. A. (2020). Physiological responses to maximal eating in men. *The British Journal of Nutrition*, *124*(4), 407–417.

Hervé, J., Mani, S., Behrman, J. R., Nandi, A., Lamkang, A. S., & Laxminarayan, R. (2022). Gender gaps in cognitive and noncognitive skills among adolescents in india. *Journal of Economic Behavior & Organization*, *193*, 66–97.

Holbein, J. B., Schafer, J. P., & Dickinson, D. L. (2019). Insufficient sleep reduces voting and other prosocial behaviours. *Nature human behaviour*, *3*(5), 492–500.

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Ishizeki, A., Kishino, T., Ogura, S., Kuga, H., Masai, Y., Harashima, K., Nakajima, S., Otaki, J., Ohnishi, H., & Watanabe, T. (2019). Influence of breakfast on hemodynamics after lunch–a sonographic evaluation of mesenteric and cervical blood flows. *Clinical Physiology and Functional Imaging*, *39*(3), 226–229.

Jagnani, M. (2022). Children's Sleep and Human Capital Production. *The Review of Economics and Statistics*, 1–45.

Jalava, N., Joensen, J. S., & Pellas, E. (2015). Grades and rank: Impacts of non-financial incentives on test performance. *Journal of Economic Behavior & Organization*, *115*, 161–196.

Jin, L., & Ziebarth, N. R. (2020). Sleep, health, and human capital: Evidence from daylight saving time. *Journal of Economic Behavior & Organization*, *170*, 174–192.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000). Losing sleep at the market: The daylight saving anomaly. *American Economic Review*, *90*(4), 1005–1011.

Kim, S. W., & Lee, B. I. (2009a). Metabolic state, neurohormones, and vagal stimulation, not increased serotonin, orchestrate postprandial drowsiness. *Bioscience Hypotheses*, *2*(6), 422–427.

Kim, S. W., & Lee, B. I. (2009b). Metabolic state, neurohormones, and vagal stimulation, not increased serotonin, orchestrate postprandial drowsiness. *Bioscience Hypotheses*, *2*(6), 422–427.

Kohlberg, L. (1976). Moral stages and moralization: The cognitive-development approach. *Moral development and behavior: Theory research and social issues*, 31–53.

Lehrskov, L. L., Dorph, E., Widmer, A. M., Hepprich, M., Siegenthaler, J., Timper, K., & Donath, M. Y. (2018). The role of IL-1 in postprandial fatigue. *Molecular Metabolism*, *12*, 107–112.

Lo, J. C., Ong, J. L., Leong, R. L., Gooley, J. J., & Chee, M. W. (2016). Cognitive performance, sleepiness, and mood in partially sleep deprived adolescents: The need for sleep study. *Sleep*, *39*(3), 687–698.

Lovato, N., & Lack, L. (2010). The effects of napping on cognitive functioning. *Progress in brain research*, *185*, 155–166.

Mani, S., Hoddinott, J., & Strauss, J. (2012). Long-term impact of investments in early schooling—Empirical evidence from rural Ethiopia. *Journal of Development Economics*, *99*(2), 292–299.

Michels, N., Vynckier, L., Moreno, L. A., Beghin, L., De La O, A., Forsner, M., Gonzalez-Gross, M., Huybrechts, I., Iguacel, I., Kafatos, A., et al. (2018). Mediation of psychosocial determinants in the relation between socio-economic status and adolescents' diet quality. *European journal of nutrition*, *57*, 951–963.

Monk, T. H. (2005). The post-lunch dip in performance. *Clinics in sports medicine*, *24*(2), e15–e23.

Mullette-Gillman, O. A., Leong, R. L. F., & Kurnianingsih, Y. A. (2015). Cognitive Fatigue Destabilizes Economic Decision Making Preferences and Strategies. *PLOS ONE*, *10*(7), e0132022.

Muralidharan, K., Singh, A., & Ganimian, A. J. (2019). Disrupting education? experimental evidence on technology-aided instruction in india. *American Economic Review*, *109*(4), 1426–1460.

Murphy, K. R., Deshpande, S. A., Yurgel, M. E., Quinn, J. P., Weissbach, J. L., Keene, A. C., Dawson-Scully, K., Huber, R., Tomchik, S. M., & Ja, W. W. (2016). Postprandial sleep mechanics in Drosophila. *eLife*, *5*, e19334.

Nagano, K., Kinoshita, F., & Touyama, H. (2022). Quantitative Evaluation of Post-Lunch Dip Using Event-Related Potential. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, *26*(1), 67–73.

Nagashima, S., Suwazono, Y., Okubo, Y., Uetani, M., Kobayashi, E., Kido, T., & Nogawa, K. (2007). Working hours and mental and physical fatigue in Japanese workers. *Occupational Medicine*, *57*(6), 449–452.

Park, J., Kim, Y., Chung, H. K., & Hisanaga, N. (2001). Long Working Hours and Subjective Fatigue Symptoms. *Industrial health*, *39*(3), 250–254.

Pollitt, E., Gorman, K. S., Engle, P. L., Martorell, R., Rivera, J., Wachs, T. D., & Scrimshaw, N. S. (1993). Early supplementary feeding and cognition: Effects over two decades. *Monographs of the Society for Research in child development*, i–118.

Pope, N. G. (2016). How the time of day affects productivity: Evidence from school schedules. *Review of Economics and Statistics*, *98*(1), 1–11.

Rao, G., Redline, S., Schilbach, F., Schofield, H., & Toma, M. (2021). Informing sleep policy through field experiments. *Science*, *374*(6567), 530–533.

Reyner, L. A., Wells, S. J., Mortlock, V., & Horne, J. A. (2012). 'Post-lunch' sleepiness during prolonged, monotonous driving — Effects of meal size. *Physiology & Behavior*, *105*(4), 1088–1091.

Roberts, R. E., Roberts, C. R., & Chen, I. G. (2001). Functioning of adolescents with symptoms of disturbed sleep. *Journal of Youth and Adolescence*, *30*(1), 1–18.

Schady, N., Behrman, J., Araujo, M. C., Azuero, R., Bernal, R., Bravo, D., Lopez-Boo, F., Macours, K., Marshall, D., & Paxson, C. (2015). Wealth gradients in early childhood cognitive development in five Latin American countries. *Journal of Human Resources*, *50*(2), 446–463.

Schilbach, F., Schofield, H., & Mullainathan, S. (2016). The psychological lives of the poor. *American Economic Review*, *106*(5), 435–440.

Shah, M., & Steinberg, B. M. (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, *125*(2), 527–561.

Shukla, C., & Basheer, R. (2016). Metabolic signals in sleep regulation: Recent insights. *Nature and Science of Sleep*, *8*, 9–20.

Sievertsen, H. H., Gino, F., & Piovesan, M. (2016). Cognitive fatigue influences students' performance on standardized tests. *Proceedings of the National Academy of Sciences*, *113*(10), 2621–2624.

Slama, H., Deliens, G., Schmitz, R., Peigneux, P., & Leproult, R. (2015). Afternoon Nap and Bright Light Exposure Improve Cognitive Flexibility Post Lunch. *PLoS ONE*, *10*(5), e0125359.

Smith, A. P., & Miles, C. (1986). The effects of lunch on cognitive vigilance tasks. *Ergonomics*, *29*(10), 1251–1261.

Stahl, M. L., Orr, W. C., & Bollinger, C. (1983). Postprandial sleepiness: Objective documentation via polysomnography. *Sleep*, *6*(1), 29–35.

Steinberg, L. (2005). Cognitive and affective development in adolescence. *Trends in cognitive sciences*, *9*(2), 69–74.

Sutter, M., Zoller, C., & Glätzle-Rützler, D. (2019). Economic behavior of children and adolescents – A first survey of experimental economics results. *European Economic Review*, *111*, 98–121.

Sweller, J. (1988). Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science*, *12*(2), 257–285.

Sweller, J., Van Merrienboer, J. J., & Paas, F. G. (1998). Cognitive architecture and instructional design. *Educational psychology review*, *10*, 251–296.

Takahashi, M., Ozaki, M., Kang, M.-I., Sasaki, H., Fukazawa, M., Iwakami, T., Lim, P. J., Kim, H.-K., Aoyama, S., & Shibata, S. (2018). Effects of meal timing on postprandial glucose metabolism and blood metabolites in healthy adults. *Nutrients*, *10*(11), 1763.

Tamiru, D., Argaw, A., Gerbaba, M., Ayana, G., Nigussie, A., & Belachew, T. (2016). Household food insecurity and its association with school absenteeism among primary school adolescents in Jimma zone, Ethiopia. *BMC public health*, *16*(1), 1–8.

Van Merrienboer, J. J., Schuurman, J. G., de Croock, M. B., & Paas, F. (2002). Redirecting learners' attention during training: Effects on cognitive load, transfer test performance and training efficiency. *Learning and instruction*, *12*(1), 11–37.

Vlahoyiannis, A., Giannaki, C. D., Sakkas, G. K., Aphamis, G., & Andreou, E. (2021). A Systematic Review, Meta-Analysis and Meta-Regression on the Effects of Carbohydrates on Sleep. *Nutrients*, *13*(4), 1283.

Vos, M., Deforche, B., Van Kerckhove, A., Michels, N., Geuens, M., & Van Lippevelde, W. (2022). Intervention strategies to promote healthy and sustainable food choices among parents with lower and higher socioeconomic status. *BMC Public Health*, *22*(1), 2378.

Wagner, D. T., Barnes, C. M., Lim, V. K., & Ferris, D. L. (2012). Lost sleep and cyberloafing: Evidence from the laboratory and a daylight saving time quasi-experiment. *Journal of Applied psychology*, *97*(5), 1068.

Walker, S. P., Wachs, T. D., Gardner, J. M., Lozoff, B., Wasserman, G. A., Pollitt, E., & Carter, J. A. (2007). Child development: Risk factors for adverse outcomes in developing countries. *The lancet*, *369*(9556), 145–157.

Wells, A. S., Read, N. W., Idzikowski, C., & Jones, J. (1998). Effects of meals on objective and subjective measures of daytime sleepiness. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, *84*(2), 507–515.

Wise, S. L., & DeMars, C. E. (2005). Low examinee effort in low-stakes assessment: Problems and potential solutions. *Educational assessment*, *10*(1), 1–17.

Yip, T., Wang, Y., Xie, M., Ip, P. S., Fowle, J., & Buckhalt, J. (2022). School start times, sleep, and youth outcomes: A meta-analysis. *Pediatrics*, *149*(6).

Zhang, X., Chen, X., & Zhang, X. (2021). Temperature and Low-stakes Cognitive Performance [Unpublished].

Tables

Table 1: Variable definitions

Variable name	Definitions
Panel A: Time of last meal Indices	
Distance from meal	Ranges from 1 to 5: 1 – if the respondents had a meal less than an hour before the test, 2 – if they had a meal one to two hours before the test, 3 – if they had a meal two to three hours prior to the test, 4 – if they had a meal three to four hours before the test and 5 – if they had a meal more than four hours before the examination
Treatment	Binary variable taking the value 1 if respondents had a meal less than an hour before the test, 0 if they had a meal more than an hour before taking a test
Panel B: Cognitive skills	
Native language proficiency	Ranges from 0 to 4: 0 – if the respondents cannot read letters, 1 – if they can read letters, 2 – if they can read words, 3 – if they can read sentences (grade 1 level text), and 4 – if they can read a paragraph (grade 2 level text)
English proficiency	Ranges from 0 to 4: 0 – if the respondents cannot read letters, 1 – if they can read letters, 2 – if they can read words, 3 – if they can read sentences (grade 1 level text), and 4 – if they can read a paragraph (grade 2 level text)
Math Score	Ranges from 0 to 4: 0 – if the respondents cannot read numbers, 1 – if the respondents can read one-digit numbers, 2 – if the respondents can read two-digit numbers, 3 – if the respondents can subtract, 4 – if the respondents can divide
Raven Matrices Test Score	Total number of correct responses on the 10-item Raven's test
Oral comprehension	Takes values between zero and 3: 0 – if the respondents answered wrong to all three oral comprehension questions, 1 – if the respondents answered correctly to 1 out of three questions, 2 – if the respondents answered correctly to 2 out of three questions, 3 – if the respondents answered correctly to 3 out of three questions
Panel C: Testing conditions and chronic issues	

Table 1 – continued from previous page

Variable name	Definitions
Time of test	Ranges from 7 to 22 (7am to 10pm)
Wake time	Ranges from 7 to 22 (7am to 10pm)
Fatigue	Respondents' self-rated measure of fatigue at the time of test, ranges from 1 to 5
Chronic fatigue	=1 if respondents reported feeling fatigued at least half the time in the last two weeks, 0 otherwise
Chronic sleep issues	=1 if respondents reported having trouble sleeping at least half the time in the last two weeks, 0 otherwise
Chronic concentration issues	=1 if respondents reported having trouble concentrating at least half the time in the last two weeks, 0 otherwise
Panel D: Background characteristics	
Age in years	Age in years
Male	=1 if male, 0 if female
Enrolled in school	School enrollment status of a child
Completed grades of schooling	Ranges from 0 to 15
Scheduled Caste	=1 if belongs to scheduled caste, 0 otherwise
Scheduled Tribe	=1 if belongs to scheduled tribe, 0 otherwise
Other Backward Caste	=1 if belongs to other backward caste, 0 otherwise
Hinduism	=1 if Hindu, 0 otherwise
Salaried	=1 if main source of household income is salaried work, 0 otherwise
Below Poverty Line Card	=1 if household has below poverty line card, 0 otherwise
MNREGA	=1 if household receives benefits from the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA), 0 otherwise
Age of the mother	Mother's age in years
Schooling of mother	Mother's completed grades of schooling
Household size	Number of individuals in a household
Tercile of asset index	Principal component analysis used to construct a variable recording an individual asset level. This variable is a proxy for an individual socio-economic status
Drinking water available	=1 if household has access to drinking water, 0 otherwise
Lighting available	=1 if household has access to lighting, 0 otherwise
Cooking fuel available	=1 if household has access to cooking fuel, 0 otherwise
Toilets available	=1 if household has access to toilets, 0 otherwise
grandparents in HH	=1 if household has access to grandparents in the household, 0 otherwise

Table 2: Summary statistics

Variable	Mean (sd)
Panel A: Time of last meal Indices	
Distance from meal	2.35
	(1.261)
Treatment	0.33
	(0.470)
Panel B: Cognitive skills	
Native language proficiency	3.30
	(1.002)
English proficiency	3.73
	(1.375)
Math Score	3.09
	(1.004)
Raven's Matrices Test Score	6.26
	(2.708)
Oral comprehension	1.98
	(0.756)
Panel C: Testing conditions and chronic issues	
Time of test	14.15
	(2.561)
Wake time	6.15
	(1.012)
Fatigue	2.46
	(0.845)
Chronic fatigue	0.05
	(0.225)
Chronic sleep issues	0.08
	(0.272)
Chronic concentration issues	0.05
	(0.221)
Panel D: Background characteristics	
Age in years	16.46
	(2.387)
Male	0.57
	(0.495)
Enrolled in school	1.07
	(0.252)
Completed grades of schooling	5.24
	(2.131)

Table 2 – continued from previous page

Variable	Mean (sd)
Scheduled Caste	0.23
	(0.419)
Scheduled Tribe	0.11
	(0.312)
Other Backward Caste	0.62
	(0.486)
Hinduism	0.87
	(0.339)
Salaried	0.46
	(0.499)
Benefits from Below Poverty Line Card	0.93
	(0.252)
Benefits from MNREGA	0.66
	(0.472)
Age of the mother	35.16
	(5.533)
Schooling of mother	1.84
	(3.136)
Household size	5.03
	(1.763)
Tercile of asset index	1.99
	(0.820)
Drinking water available	0.98
	(0.146)
Lighting available	1.00
	(0.0412)
Cooking fuel available	0.34
	(0.474)
Toilets available	0.27
	(0.444)
grandparents in HH	0.09
	(0.289)
Observations	4,112

Table 3: Normalized differences of background characteristics

	Mean Treatment (1)	Mean Control (2)	Difference (standard error) (3)	Normalized difference (4)=(3)-(2)
Age in years	16.03	16.67	-0.428***	0.30
	(2.426)	(2.340)	(0.077)	
Sharpened q-values			[0.002]	
Male	0.56	0.57	-0.030*	0.05
	(0.497)	(0.495)	(0.017)	
Sharpened q-values			[>0.1]	
Enrolled in school	1.06	1.07	0.001	0.05
	(0.244)	(0.256)	(0.008)	
Sharpened q-values			[>0.1]	
Completed grades of schooling	5.26	5.24	-0.115	0.02
	(2.115)	(2.139)	(0.072)	
Sharpened q-values			[>0.1]	
Scheduled Caste	0.22	0.23	-0.034**	0.00
	(0.416)	(0.420)	(0.014)	
Sharpened q-values			[>0.1]	
Scheduled Tribe	0.07	0.13	0.002	0.22
	(0.253)	(0.335)	(0.007)	
Sharpened q-values			[>0.1]	
Other Backward Caste	0.65	0.60	0.027*	0.09
	(0.477)	(0.490)	(0.015)	
Sharpened q-values			[>0.1]	
Hinduism	0.86	0.87	0.015	0.05
	(0.350)	(0.333)	(0.011)	
Sharpened q-values			[>0.1]	
Salaried	0.43	0.48	-0.037**	0.16
	(0.495)	(0.500)	(0.016)	
Sharpened q-values			[>0.1]	
Below Poverty Line Card	0.96	0.92	-0.005	0.19
	(0.196)	(0.274)	(0.007)	
Sharpened q-values			[>0.1]	
MNREGA	0.71	0.64	-0.007	0.16
	(0.452)	(0.480)	(0.013)	
Sharpened q-values			[>0.1]	
Age of the mother	34.91	35.29	-0.139	0.09
	(5.335)	(5.625)	(0.183)	
Sharpened q-values			[>0.1]	
Schooling of mother	1.75	1.89	-0.020	0.03
	(3.101)	(3.152)	(0.099)	
Sharpened q-values			[>0.1]	
Household size	4.99	5.05	0.071	0.05

Table 3 – continued from previous page

	Mean Treatment (1)	Mean Control (2)	Difference (standard error) (3)	Normalized difference (4)=(3)-(2)
	(1.757)	(1.766)	(0.057)	
Sharpened q-values			[>0.1]	
Tercile of asset index	2.01	1.98	-0.009	0.04
	(0.807)	(0.827)	(0.025)	
Sharpened q-values			[>0.1]	
Drinking water available	0.99	0.97	0.009**	0.03
	(0.121)	(0.157)	(0.004)	
Sharpened q-values			[>0.1]	
Lighting available	1.00	1.00	-0.002	0.01
	(0.0470)	(0.0381)	(0.001)	
Sharpened q-values			[>0.1]	
Cooking fuel available	0.37	0.33	-0.007	0.09
	(0.483)	(0.469)	(0.013)	
Sharpened q-values			[>0.1]	
Toilets available	0.27	0.27	0.006	0.00
	(0.444)	(0.445)	(0.013)	
Sharpened q-values			[>0.1]	
Grandparents in HH	0.08	0.10	0.001	0.05
	(0.278)	(0.294)	(0.010)	
Sharpened q-values			[>0.1]	
Observations	1,355	2,757		

Notes: Columns (1) and (2) report means of background characteristics in the treatment and control groups respectively. Column (3) contains the resulting coefficients from a regression of background characteristics on the treatment dummy and village fixed effects, which explains why the estimates of Column (3) sometimes differ from the differences between Columns (1) and (2). Finally, Column (4) reports normalized differences from Imbens and Rubin (2015) *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Effect of post-meal testing on test scores

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.312***	-0.244***	-0.253***	-0.470***	-0.145***
	(0.032)	(0.030)	(0.034)	(0.034)	(0.033)
Sharpened q-values	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations	4,112	4,112	4,112	4,112	4,112
R-squared	0.269	0.266	0.195	0.244	0.177
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes

Notes: Each column presents the coefficient estimates from regressions of standardized cognitive outcomes on the treatment dummy, selected covariates and village and age-group fixed effects. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Effect of post-meal testing on fatigue

	Fatigued
	(1)
Treatment	0.388***
	(0.027)
Sharpened q-value	[0.001]
Observations	4,112
R-squared	0.238
Controls	Yes
Village FE	Yes
Age-group FE	Yes

Notes: This table reports the coefficient from the regression of the standardized self-reported measure of fatigue on the treatment dummy, and similar covariates and fixed effects to those used to produce Table 4. The self-reported measure of fatigue is described in panel C of Table 1. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6: Task complexity gradient in the effect of post-meal testing

Panel A: Reading in native languages				
	Can read paragraph	Can read sentence	Can read word	Can read letter
	(1)	(2)	(3)	(4)
Treatment	-0.186***	-0.081***	-0.038***	-0.005
	(0.015)	(0.013)	(0.009)	(0.004)
Observations	4,112	4,112	4,112	4,112
R-squared	0.294	0.233	0.114	0.073
P-value from Wald-tests:				
Can read paragraph=Can read letter	<0.01			
Panel B: Reading in English				
	Can read paragraph	Can read sentence	Can read word	Can read letter
	(1)	(2)	(3)	(4)
Treatment	-0.134***	-0.138***	-0.068***	-0.007
	(0.015)	(0.015)	(0.013)	(0.005)
Observations	4,112	4,112	4,112	4,112
R-squared	0.256	0.257	0.173	0.093
P-value from Wald-tests:				
Can read paragraph=Can read letter	<0.01			
Panel C: Math				
	Can divide	Can substract	Recognize numbers 10-99	Recognize numbers 1-9
	(1)	(2)	(3)	(4)
Treatment	-0.101***	-0.050***	-0.076***	-0.009*
	(0.016)	(0.014)	(0.009)	(0.005)
Observations	4,112	4,112	4,112	4,112
R-squared	0.186	0.182	0.099	0.0475
P-value from Wald-tests:				
Can divide=Can recognize 1-9	<0.01			
Controls	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes

Notes: Each panel presents the coefficients on the treatment dummy obtained from regressions of different outcomes (listed in Columns 1-4) on the treatment dummy, selected covariates and sets of fixed effects similar to those used in Table 4. In panel A, outcome variables are dummies recording disaggregated measures of reading ability in native language, going from the most challenging to the least challenging tasks from left to right. Similarly, outcomes in panel B are binary variables recording disaggregated measures of reading ability in English. Finally, outcomes in panel C record disaggregated measures of mathematical skills, from the hardest (can divide) to the simplest task (recognize numbers). The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 7: Effect of post-meal testing on test scores, by chronic fatigue

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Panel A: No chronic fatigue					
Treatment	-0.301***	-0.229***	-0.224***	-0.443***	-0.148***
	(0.033)	(0.031)	(0.035)	(0.035)	(0.033)
Observations	3,872	3,872	3,872	3,872	3,872
R-squared	0.273	0.267	0.192	0.245	0.154
Panel B: Chronic fatigue					
Treatment	-0.451*	-0.380	-0.776***	-1.121***	-0.228
	(0.250)	(0.238)	(0.247)	(0.201)	(0.282)
Observations	221	221	221	221	221
R-squared	0.609	0.551	0.588	0.727	0.639
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes
Coefficient's p-value from treatment*Chronic fatigue interaction					
No chronic fatigue=Chronic fatigue	<0.05	<0.01	<0.01	<0.01	>0.10

Notes: This table presents the coefficient estimates obtained from regressions of cognitive outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, stratifying the sample according to chronic fatigue problems, where the chronic fatigue dummy variable takes the value 1 if a respondent reported feeling fatigued at least half the time in the last two weeks, zero otherwise. Panel A contains estimates for the sample of respondents with no chronic fatigue. Panel B reports estimates in the sample of respondent with chronic fatigue. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). The final row provides the p-values corresponding to the coefficient of the interaction between the treatment and the chronic fatigue variable in a fully interacted model. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 8: Effect of post-meal testing on test scores, by sleep issues

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Panel A: No trouble sleeping					
Treatment	-0.271***	-0.212***	-0.183***	-0.430***	-0.140***
	(0.033)	(0.032)	(0.035)	(0.035)	(0.034)
Observations	3,843	3,843	3,843	3,843	3,843
R-squared	0.268	0.268	0.189	0.240	0.169
Panel B: Trouble sleeping					
Treatment	-0.453***	-0.464***	-0.821***	-0.795***	-0.165
	(0.167)	(0.147)	(0.174)	(0.169)	(0.180)
Observations	252	252	252	252	252
R-squared	0.604	0.617	0.678	0.617	0.536
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes
Coefficient's p-value from treatment*Chronic fatigue interaction					
No trouble sleeping=Trouble sleeping	<0.01	<0.01	<0.01	<0.01	>0.10

Notes: This table presents the coefficient estimates obtained from regressions of cognitive outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, stratifying the sample according to sleep issues, where the chronic sleep dummy variable takes the value 1 if a respondent reported having trouble sleeping at least half the time in the last two weeks, zero otherwise. Panel A contains estimates for the sample of respondents with no chronic sleep issues. Panel B reports estimates in the sample of respondent with chronic sleep issues. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). The final row provides the p-values corresponding to the coefficient of the interaction between the treatment and the chronic sleep issue dummy in a fully interacted model. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Effect of post-meal testing on test scores, by time of day

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Panel A: Morning					
Treatment	-0.314***	-0.217***	-0.214***	-0.355***	-0.111**
	(0.049)	(0.046)	(0.051)	(0.051)	(0.050)
Observations	1,707	1,707	1,707	1,707	1,707
R-squared	0.325	0.278	0.240	0.274	0.216
Panel B: Afternoon					
Treatment	-0.304***	-0.299***	-0.249***	-0.579***	-0.111*
	(0.056)	(0.054)	(0.059)	(0.059)	(0.060)
Observations	1,615	1,615	1,615	1,615	1,615
R-squared	0.261	0.270	0.200	0.282	0.189
Panel C: Evening					
Treatment	-0.288***	-0.251***	-0.305***	-0.613***	-0.207***
	(0.087)	(0.081)	(0.094)	(0.090)	(0.078)
Observations	743	743	743	743	743
R-squared	0.371	0.434	0.349	0.385	0.369
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes
Coefficients' p-values from treatment*Time of day interaction					
Morning=Afternoon	>0.10	>0.10	>0.10	<0.01	>0.10
Morning=Evening	>0.10	>0.10	0.070	0.021	>0.10

Notes: This table presents the coefficient estimates obtained from regressions similar to those used to produce Table 4, stratifying the sample by the time of day, where time of day is captured through a categorical variable taking the value 1 if respondents tested between 8am and 1pm, 2 if they tested between 1pm and 5pm, and 3 if they tested after 5pm. Thus, panels A, B and C report estimates obtained in the samples of individuals who tested in the morning, afternoon and evening, respectively. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). The final rows provide the p-values corresponding to the coefficient of the interaction between the treatment and time of day variable in a fully interacted model. *** p<0.01, ** p<0.05, * p<0.10.

Table 10: Effect of post-meal testing on test scores, by SES

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Panel A: SES Tercile 1					
Treatment	-0.100	-0.092	-0.106	-0.290***	-0.289***
	(0.065)	(0.062)	(0.065)	(0.061)	(0.067)
Observations	1,394	1,394	1,394	1,394	1,394
R-squared	0.269	0.259	0.197	0.252	0.176
Panel B: SES Tercile 2					
Treatment	-0.392***	-0.279***	-0.244***	-0.463***	-0.064
	(0.057)	(0.052)	(0.059)	(0.061)	(0.057)
Observations	1,342	1,342	1,342	1,342	1,342
R-squared	0.314	0.309	0.238	0.284	0.284
Panel C: SES Tercile 3					
Treatment	-0.473***	-0.403***	-0.396***	-0.602***	-0.102**
	(0.050)	(0.046)	(0.056)	(0.059)	(0.051)
Observations	1,367	1,367	1,367	1,367	1,367
R-squared	0.350	0.353	0.293	0.355	0.242
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes
Coefficients' p-values from treatment*SES Tercile					
SES Tercile 1=SES Tercile 2	<0.01	<0.01	0.045	0.042	0.043
SES Tercile 1=SES Tercile 3	<0.01	<0.01	<0.01	<0.01	>0.10

Notes: This table reports the coefficient estimates obtained from regressions of cognitive outcomes on the treatment dummy, selected covariates and sets of fixed effects similar to those used to produce Table 4, now stratifying the sample by socio-economic status, where socio-economic status is captured through terciles of an asset index built via principal component analysis. Panels A, B and C report estimates obtained in the samples of individuals belonging to the first, second and third terciles of the asset index, respectively. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). The final rows provide the p-values corresponding to the coefficient of the interaction between the treatment and the SES tercile index in a fully interacted model. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 11: Effect of post-meal testing on test scores, by gender

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Panel A: Female					
Treatment	-0.369***	-0.281***	-0.257***	-0.510***	-0.206***
	(0.052)	(0.048)	(0.053)	(0.053)	(0.051)
Observations	1,774	1,774	1,774	1,774	1,774
R-squared	0.310	0.318	0.241	0.278	0.225
Panel B: Male					
Treatment	-0.280***	-0.229***	-0.237***	-0.443***	-0.092**
	(0.042)	(0.040)	(0.045)	(0.046)	(0.044)
Observations	2,336	2,336	2,336	2,336	2,336
R-squared	0.269	0.261	0.194	0.254	0.184
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes
Coefficient's p-value from treatment*male interaction					
Male=Female	>0.10	>0.10	>0.10	>0.10	>0.10

Notes: This table presents the coefficient estimates obtained from regressions of cognitive outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, stratifying the sample by gender. Panel A contains estimates for the female sample. Panel B reports estimates in the male sample. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (12-14), middle adolescence (15-17), and young adults (18-22). The final row provides the p-values corresponding to the coefficient of the interaction between the treatment and the male dummies in a fully interacted model. *** p<0.01, ** p<0.05, * p<0.10.

Table 12: Effect of post-meal testing on test scores, by age category

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Panel A: Early-adolescence					
Treatment	-0.269***	-0.273***	-0.403***	-0.503***	-0.483***
	(0.073)	(0.061)	(0.076)	(0.071)	(0.073)
Observations	877	877	877	877	877
R-squared	0.374	0.353	0.310	0.319	0.336
Panel B: Middle-adolescence					
Treatment	-0.313***	-0.204***	-0.200***	-0.448***	-0.049
	(0.049)	(0.047)	(0.052)	(0.052)	(0.051)
Observations	1,925	1,925	1,925	1,925	1,925
R-squared	0.253	0.250	0.206	0.237	0.199
Panel C: Young adults					
Treatment	-0.278***	-0.225***	-0.163***	-0.453***	0.046
	(0.054)	(0.057)	(0.058)	(0.062)	(0.055)
Observations	1,286	1,286	1,286	1,286	1,286
R-squared	0.244	0.299	0.260	0.260	0.239
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Coefficients' p-values from treatment*male interaction					
Early adolescence=Middle adolescence	>0.10	>0.10	0.024	>0.10	<0.01
Early adolescence=Young adults	>0.10	>0.10	<0.01	>0.10	<0.01

Notes: This table presents the coefficient estimates obtained from regressions of cognitive outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, stratifying the sample by age group, where age-groups are early adolescence (12-14) in panel A, middle adolescence (15-17) in panel B, and young adults (18-22) in panel C, respectively. The control variables included in the regressions are described in panel D of Table 1. The final rows provide the p-values corresponding to the coefficient of the interaction between the treatment and the age category index in a fully interacted model. *** p<0.01, ** p<0.05, * p<0.10.

Online Appendix

Table A1: Placebo check: Effect of post-meal testing on gender attitudes

	Gender roles	Freedom	Education	Leadership
	(1)	(2)		
Treatment	-0.020	-0.000	-0.029	0.021
	(0.032)	(0.031)	(0.030)	(0.030)
Observations	4,107	4,110	4,105	4,109
R-squared	0.216	0.282	0.292	0.275
Controls	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes

Notes: This table presents the coefficient estimates obtained from regressions of gender attitude outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, replacing outcome variables by the gender attitude outcomes used by Hervé et al. (2022). The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (10-13), middle adolescence (14-17), and young adults (18-22). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A2: Effect of post-meal testing on test scores, alternative definition of treatment

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.297***	-0.205***	-0.244***	-0.384***	-0.036
	(0.031)	(0.029)	(0.033)	(0.033)	(0.032)
Observations	4,112	4,112	4,112	4,112	4,112
R-squared	0.269	0.264	0.195	0.234	0.173
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the coefficient estimates obtained from regressions of outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, redefining the treatment dummy to take a value 1 if a respondent had a meal in the two hours preceding a test, and 0 if her last meal happened more than two hours before she was interviewed. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (10-13), middle adolescence (14-17), and young adults (18-22). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A3: Effect of post-meal testing on test scores, in Magic Bus' control villages

	Reading score in native language	Reading score in English	Math score	Raven's test score	Oral comprehension score
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.172***	-0.179***	-0.131**	-0.242***	-0.239***
	(0.062)	(0.061)	(0.065)	(0.063)	(0.064)
Observations	1,245	1,245	1,245	1,245	1,245
R-squared	0.298	0.210	0.201	0.226	0.272
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the coefficient estimates obtained from regressions of outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4, in the sample of individuals belonging to the control villages of the Magic Bus program. The control variables included in the regressions are described in panel D of Table 1. Age-group fixed effects respectively correspond to early adolescence (10-13), middle adolescence (14-17), and young adults (18-22). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.