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Abstract

Food coma, also known as postprandial somnolence, is a commonly cited reason for experiencing reduced alertness during mid-afternoon worldwide. By using exogenous variation in the timing of tests and, hence, by extension, plausibly exogenous variation in the temporal distance between an individual's last meal and the time of test, we examine the causal impact of postprandial somnolence on cognitive capacities. Analyzing novel time use data on $\sim$ 4,600 Indian adolescents and young adults, we find that testing within an hour after a meal reduces test-takers' scores on English, native language, math, and Raven's tests by 8, 8, 8, and 16 percent, respectively, compared to test-takers who took the tests more than an hour after their meal. We further find that the negative effect of postprandial somnolence on cognition operates through increased feelings of fatigue and depletion of cognitive resources that become more pronounced while dealing with more challenging test questions.

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

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1 Introduction

Standardized tests on language, math, and analytical reasoning have become indispensable for assessing childrens' cognitive capacities 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 contents, and scoring procedures are identical for all test-takers. Because of these features, standardized tests are globally trusted to give unbiased representations of cognitive skills and are often used to evaluate the effectiveness of a wide range of 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 (Bettinger, 2012; Jalava et al., 2015; Gneezy et al., 2019), environmental factors including contemporaneous temperature (Park, 2018; Zhang et al., 2021) and pollution (Ebenstein et al., 2016), and the time of day (Goldstein et al., 2007; Dills and Hernandez-Julian, 2008; Sievertsen et al., 2016; Pope, 2016; Williams and Shapiro, 2018; Lusher et al., 2019; Gaggero and Tommasi, 2023) are found to impact performance on cognitive tests. The time-of-day effects documented in the literature exploit variations in class timings, testing conditions (e.g., testing after breaks), and natural fluctuations in test-takers' circadian rhythms. Yet, no study has formalized the effect of another temporary source of reduced alertness commonly experienced worldwide, namely, digestive fatigue or food coma, on test scores.

Food coma, commonly referred to as the "postprandial dip", is a feeling of tiredness that is observed after consuming a meal. In the medical literature, the term "postprandial" refers to phenomena that occurs after eating and the postprandial dip 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 primarily 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 in advance, which can result in behavioral responses such as drinking caffeine or abstaining from a large meal to minimize the influence of food coma on test scores and job performance. Thus, it is only when the time of test is truly unknown to the test-taker that the estimated causal impact of food coma on standardized tests are not conflated by individual behavioral responses. Second, data sets on test scores do not typically capture information on the time of the test-takers' last meal, making it impossible for researchers to examine the impact of food coma on test performance. Third, most administrative data sets that have been used to explore the effect of test timing do not capture information on subjective feelings of tiredness. Consequently, there are no data and empirical evidence on the key underlying mechanism posited in the literature for driving the effects of postprandial dip, namely, fatigue. (Roberts et al., 2001; Monk, 2005; Reyner et al., 2012; Chaturvedi et al., 2021).

In this study, we overcome these limitations by using exogenous variation in the timing of tests and hence, by extension, plausibly exogenous variation in the temporal distances between the times of tests and the test takers' last meal, to identify the causal impact of postprandial testing on cognitive performance. We examine the impact of postprandial somnolence on cognition among the rural poor in India, which is a particularly sleep-deprived context, and thus, an environment in which the detrimental effects of food coma could magnify pre-existing disparities associated with poverty in a range of outcomes such as attention, well-being, and cognitive performance (Bessone et al., 2021; Walker, 2017). We collected data on testing conditions and test scores for approximately 4,600 adolescents and young adults between the ages of 12 and 22 years from two rural districts in Maharashtra and Andhra Pradesh in India. The times at which interviewers visit households are exogenous, that is, determined by the number of enumerators and a field plan for the day and do not use any pre-existing information on child and household characteristics such as education or income. Furthermore, we only use data from adolescents and young adults available during an enumerator's first visit to a household as second visits could be correlated with unobserved household characteristics that also determine parental investments in individuals' cognitive attainment. Hence, all the different times at which the enumerators visit a household for the first time are as good as randomly determined. 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 tests, among which we recorded the times at which respondents woke up and the times at which they ate their last meals. Medical research suggests that the effects of the postprandial dip peak approximately thirty to sixty minutes after meals (Alleman Jr and Bloomer, 2011; Takahashi et al., 2018).[1] Hence, we compare the performance of two groups – individuals who had their meals within an hour of the tests and individuals who took the tests more than an hour after their last meal. Specifically, we assess the causal effect of postprandial dip/food coma on adolescents' performances on a wide range of tests including reading, math, oral comprehension, and fluid intelligence that capture multidimensional aspects of learning.

Our results suggest that postprandial somnolence considerably decreases respondents' measured cognitive skills. Respondents who took tests less than an hour after their last meals perform significantly worse than individuals who took tests more than an hour after their last meal. Specifically, in comparison to individuals who took the exams more than an hour after they last ate, individuals who took the exams within an hour of their last meal scored 0.27 ($\sim$ 8 percent), 0.21 ($\sim$ 8 percent), 0.25 ($\sim$ 8 percent), 0.42 ($\sim$ 17 percent), and 0.15 ($\sim$ 5 percent) standard deviations lower on reading tests in native and English languages, math tests, fluid intelligence, and oral comprehension tests, respectively. Next, we find that the effect of postprandial testing varies by task difficulty. The negative effects of postprandial testing on cognitive performance are much stronger when test questions are more challenging. Testing within an hour after a meal decreases measured native-language reading proficiency by 18 percent for paragraphs, 7 percent for sentences, and 4 percent for individual words. A similar pattern is also observed on the math test. Finally, we show

[1] Figure 1 corroborates this finding.

that the negative effects of food coma on cognition mainly operate through increased post-meal fatigue. Specifically, testing less than an hour after meals increases students' level of reported fatigue[2] by 0.39 ($\sim$ 13 percent) standard deviations compared to students who took the tests more than an hour after their last meals. This increase in fatigue could lead to lower test scores through reduced alertness and the depletion of individuals' cognitive resources, or reduced effort on tests. We find suggestive evidence of the former channel.

These impacts align with findings from the literature on the effects of effort and sleep on performance on cognitive tests. For example, Gneezy et al., 2019 show that small cash incentives at the times of tests increase performance on tests by 13 percent, compared to students who were not incentivized to exert effort. Additionally, our findings align with the existing medical evidence showing that sleepiness inhibits individuals' cognitive capacities to solve problems (Roberts et al., 2001; Alhola and Polo-Kantola, 2007; Reyner et al., 2012; Lo et al., 2016).

Our results suggest that food coma is a significant and sizeable cause of reduced alertness/cognitive fatigue that inhibits students' performance on cognitive tests. Our novel findings make several contributions to the economics literature. First, this study adds to the nascent and relatively scarce literature on the causes of fatigue and its economic effects. Studies examining 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 prior study has considered the postprandial dip as a source of fatigue that can significantly alter individuals' cognitive functioning. Towards this end, we broaden the existing body of literature on the cognitive repercussions of fatigue (Ebenstein et al., 2016): By using unique data on students' performance, times of tests, and times of

[2] Respondent's self-rated measure of fatigue at the time of test ranges from 1 to 4.

last meals, we are able to investigate the causal effect of postprandial dip on test scores.

Second, by showing that the effects of food coma worsen with task difficulty, our findings also align with the literature on attention and cognitive load, which highlight the negative effects of cognitive burden on learning (Sweller, 1988). In our context, high-difficulty tasks make the negative effects of postprandial fatigue more salient by increasing respondents' cognitive loads. In other words, the postprandial dip might deplete individual cognitive resources and sleep may be necessary 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. Specifically, our findings help reconcile Bessone et al. (2021)'s surprising result that daytime 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 repair the intellectual capacities that were partially exhausted during the post-meal digestive period - an important source of reduced alertness during the mid-afternoon.

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 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, our findings suggest that the socioeconomic status (SES) gaps in student achievement reported in the literature might be underestimated (Fernald et al., 2011; Schady et al., 2015; Hervé et al., 2022), as food coma systematically reduces high SES respondents' performance more than low SES respondents possibly due to differences in meal compositions.

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. Section 6 concludes.

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, the 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, however, has 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). In addition to this hypothesis, an alternative theory is that food coma is part of humans' bi-circadian rhythm, in which individuals experience a 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 are important in the context of our sample, we further address them in Section 4.4. 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).

Overall, 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). Complementary 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). Yet no prior study has formally investigated the effects of the post-meal dips on cognition. By addressing this gap, our study makes a valuable addition to both educational research and, by extension, labor economics research since students' performances on standardized tests are an important predictor of success in the labor market.

3 Data

3.1 Sample description

This paper leverages the endline household and individual surveys from 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-

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

November 2015, we collected baseline data on youth 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 2022.

In this paper, we use the endline individual-level surveys administered to adolescents and young adults who were between the ages of 12 and 22 years in 2022. These surveys provide information on the respondents' ages, sex, school enrollment status, completed grades of schooling, work status, 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 used to evaluate cognitive skills among children and adolescents (Banerji et al., 2013; Shah and Steinberg, 2017; Muralidharan et al., 2019). In the math tests, we assessed 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 individuals' ability to read a paragraph, sentence, words, and letters. Additionally, we also used Raven's progression matrices to measure analytical skills (Dasgupta et al., 2022). Raven's tests are used to capture fluid intelligence, in contrast to the ASER reading tests which measure crystallized intelligence. Finally, we implemented a unique set of oral comprehension tests in which respondents were read a short passage and were then asked three questions about the narrative. This assessment is important as several tasks in low-income countries rely on oral comprehension.

During the individual-level endline surveys only, we also collected data on respondents' time use around the time of the tests. In particular, 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.[4] The plausible exogeneity of the test times is particularly important since we exploit random variation in test timing to identify the effect of post-meal testing on test scores. Finally, the time use section of the survey gathered information about respondents' activities before taking the tests: we asked respondents at what time they woke up on the day of the test and we recorded a self-reported measure of fatigue that, to our knowledge, has never been collected in this context before – how tired the respondent currently felt on a scale of 1 to 4. Crucially for the purpose of this analysis, we also 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.[5] The baseline survey gathered data on household demographics such as age, gender, schooling levels, and work status of household members, as well as socioeconomic status, assets, and participation in social protection programs.

3.2 Variable definitions

Time of last meal: We collect 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

[4]A possible concern is whether enumerators began their work from the village center and moved outward, and if the distribution of residences were simultaneously related to background characteristics such as caste status or socioeconomic status. This physical segregation based on background characteristics could challenge our identification strategy. However, we are able to rule it out by showing that background characteristics such as socioeconomic status do not predict the time of household visits in Appendix Table A1 and Appendix Figure A1. We also obtained confirmation from the survey firm that fieldwork plans did not follow specific geographic patterns.

[5]In 2022, 20% of the sample was between the ages of 10 and 13 years, 47% between the ages of 14 and 17 years, and 32% between the ages of 18 and 22 years.

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 a "treatment" dummy that takes the 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.

Cognitive skills: We create five outcome variables to capture respondents' performance 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 respondents' scores on reading tests in their native language and English. The scores in these tests range from 0 to 4: (0) if respondent cannot read letters, (1) if they can 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: (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 respondents' 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 incorrectly, (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.

Testing conditions: We collect novel data on respondents' time use before taking the tests. First, we record continuous measures of the time of day at which respondents woke in the morning and the time of day the respondents take the tests. In addition, we construct a variable that captures 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.

Background characteristics: We present a full list of household and individual-level characteristics in Panel D, Table 1. Most of these measures[6] are obtained from the 2015

[6]With the exception of current age and salaried status, which are measured at endline (2022). The rationale for using mostly baseline characteristics is that we do not have household characteristics at

survey, that is, the baseline survey, and hence, by construction, must be uncorrelated with the timings of tests, which are quasi-random. At the individual level, we control for respondents' age, 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 control for household size, presence of grandparents in the household, access to infrastructure (such as, availability of drinking water, lighting, cooking fuel, and toilets), caste category, religion, and access to social protection programs.

3.3 Summary Statistics

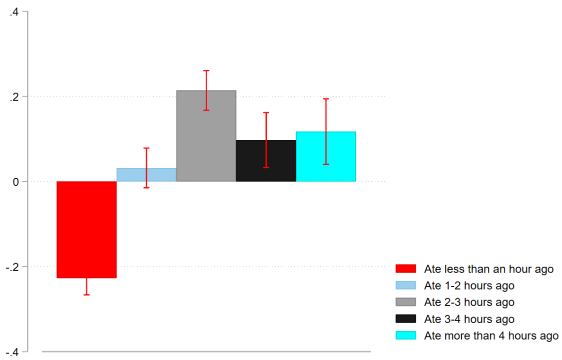
We report summary statistics on all outcome variables and demographic variables in Table 2. In Table 3, we further check if the baseline household and individual background characteristics are similar between the treatment group (those who were tested within an hour from their last meal) and the control 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 significant at the 1 percent level or 5 percent level, except for age, the scheduled-caste dummy and employment status. Since statistical significance increases in sample size and the number of outcomes tested, we also present adjusted q-values (Anderson, 2008; Benjamini et al., 2006a) in Column (3) in brackets, and find that almost all differences between the treatment and control groups disappear, except for age.[7] 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. Finally, we further alleviate possible selection concerns by examining the distribution of surveys conducted at different times of the day and regressing the times of surveys on demographic characteristics. These robustness checks allow us to confirm that individuals

endline.

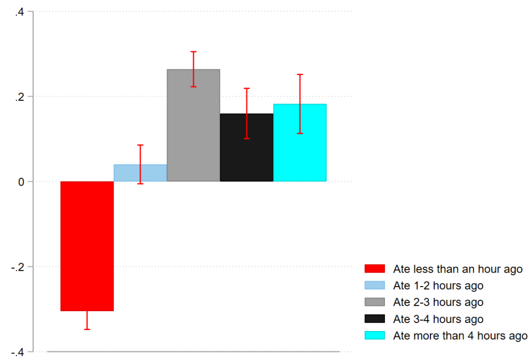
[7] Individuals in the treatment group are on average six months younger than those in the control group.

with specific traits do not select into specific time slots for their surveys. We find that the distribution of surveys is relatively uniform across hours of the day – see Appendix Figure A2. We also find that most baseline demographic characteristics do not predict test times – see Appendix Table A1 and Appendix Figure A1.

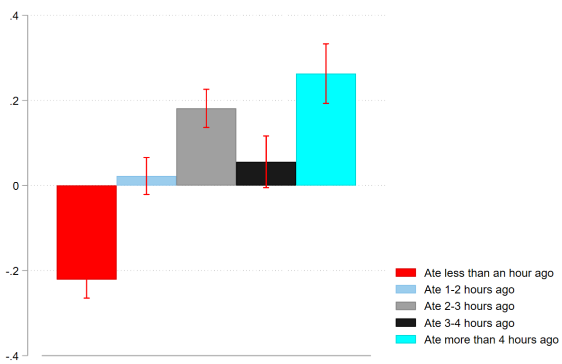
Next, in Figure 1 we show how performance on tests evolves with distance from the meal. We report standardized average reading scores in native languages, reading scores in English, oral comprehension scores, Raven's scores, and math scores by time since last meal. Scores are standardized with respect to the sample group means and standard deviations. We find a steep gradient in students' 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 compared to students who took tests more than an hour after their last meals.



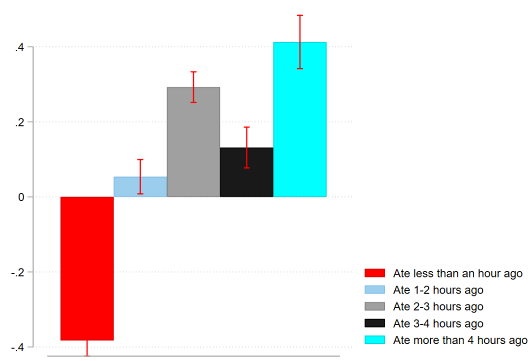
(a) Reading score in English



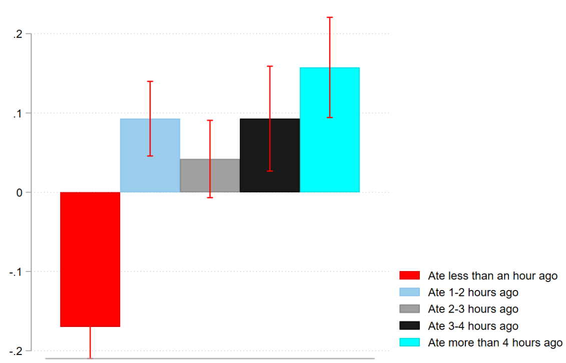
(b) Reading score in native language



(c) Math score



(d) Raven's score



(e) Oral comprehension score

Figure 1: Cognitive attainment by time distance from last meal

4 Results

4.1 Empirical specification

To examine the effect of post-meal testing, we estimate the following linear regression model using ordinary least squares (OLS):

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

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 means and standard deviations of the control group, the β coefficients can be interpreted in terms of standard deviation units of the control group. $X_{i,hh}$ contains the full set of baseline demographic characteristics described in Panel D of Table 1. We also control for village fixed effects via ϕ_v and age-group[8] fixed effects via μ_a. The village fixed effects control for village-level factors such as the quality of local schools or local climate shocks such as rainfall or temperature patterns. The age-group fixed effects are included to account for pre-existing age differences between the treatment and the control group.

4.2 Impact on Cognitive Outcomes

Table 4 presents the main findings of the paper, that is, the estimated 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 0.27, 0.21, 0.25, 0.42, 0.15 standard deviations, respectively, compared to the control group who

[8]Age-groups are early adolescence (12-14), middle adolescence (15-17), and young adults (18-22).

were tested more than an hour after their last meals. Because effect sizes based on standard deviations depend on the control group variation, we translate our estimates in percentage terms (Singh, 2015). The effect sizes are substantial – they suggest that individuals who tested less than an hour after meals scored 8 percent lower in reading in native language, 8 percent lower in reading in English, 8 percent lower in mathematics, 16 percent lower in fluid intelligence, and 6 percent lower in oral comprehension compared to the control group. To put these results in perspective, our findings are comparable to Muralidharan et al. (2019)'s findings that a personalized technology-aided instruction program increased the ability of test-takers in the treatment group to perform arithmetic computations and complete a sentence by 12 and 6.4 percent, respectively, compared to their counterparts in the control group; and Gneezy et al. (2019)'s findings that providing surprise financial incentives increased students' performance on tests by 13 percent compared to a group of non-incentivized students.[9] We explain the noticeably large effect sizes on Raven's scores by the fact that children in rural India are not used to taking tests that require them to solve problems in an abstract non-verbal way (de Barros and Ganimian, 2023). Therefore, Indian children are likely to find the problems on the Raven's tests particularly challenging, which could magnify the negative effect of postprandial testing on cognitive performance. We elaborate on this result and the existence of a task difficulty gradient in the effect of postprandial testing in section 4.3. Finally, we note that our findings are robust to Type I error concerns.[10] We calculate sharpened two-stage q-values in Table 4 (Benjamini et al., 2006b; Anderson, 2008) and the observed impacts remain statistically significant at the 1 percent level.

Overall, our results suggest that testing less than or an hour after meals considerably worsens students' measured performance 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,

[9]0.24 to 0.28 standard deviations compared to a group of non-incentivized students.

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

2010; Bessone et al., 2021). Our identification of the negative effect of the postprandial dip on test performance might also explain why Bessone et al. (2021) find that daytime naps have much larger positive effects on cognition and productivity compared to increased nighttime sleep.

4.3 Mechanism

We explore fatigue as one possibly critical mechanism through which post-meal testing could impact cognitive performance. We use respondents' self-rated measure of fatigue to assess whether the negative effect of post-meal testing works through increased sleepiness after meals. In Table 5, we present the estimated causal impact of the postprandial period on reported fatigue. We find that inquiring about respondents' fatigue levels within an hour after their last meal increases reported fatigue levels by 0.39 standard deviations compared to the control group. 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).

A subsequent question is how fatigue itself impacts students' performance on tests. The effect of postprandial fatigue could operate through two different channels: Effort versus ability. On one hand, the effort channel posits that fatigue may induce individuals to feel less motivated and less willing to tackle assigned tasks. On the other hand, individuals could retain their motivation but lack the cognitive resources required to solve the problems they face. This second hypothesis suggests that fatigue impairs test scores by increasing cognitive load and depleting cognitive resources. In other words, even if individuals possess the motivation to solve test questions, they may lack the cognitive capacity to do so. One way to disentangle the effort and ability channels is to assess how the impact of post-meal testing varies with the difficulty of tasks. If the negative effect of fatigue on test performance is mediated through a depletion of cognitive resources and diminished thinking ability, we would expect the difficulty of tasks to play a significant moderating role in the impact of postprandial testing. Conversely, if the negative effect of fatigue on test performance is primarily due to reduced effort, the negative impact of postprandial testing should remain relatively consistent across task difficulty levels.

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 read a paragraph, read a sentence, read a word, and 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 perform division, perform subtraction, recognize numbers from 10-99, and recognize numbers from 1 to 9.

We find suggestive evidence of a "task complexity" gradient in the effects of post-meal testing on performance. 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 in native language by 18 percent, read a sentence by 7 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 13 percent, reading a word by 6 percent, and it has no significant impact on respondents' capacities 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 7 percent drop in the ability to recognize two-digit numbers, and does not significantly affect abilities to read one-digit numbers.

These results suggest that a big part of the effect of post-meal testing works through the ability channel: A decrease in individuals' cognitive capacities. The more difficult the test question, the more salient the effects of post-meal testing on cognitive load. 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 work through a depletion of respondents' attentional resources. When tasks require more cognitive loads 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). Additionally, we note that the finding that postprandial fatigue affects test performance through a depletion of cognitive resources is supported by the large coefficient size on the Raven's score in Table 4. Given that the Raven's tests may be more challenging compared to reading, math, or oral comprehension questions, the large coefficient on the Raven's score may be attributed to an accentuation of the detrimental effect of postprandial testing due to the higher difficulty of that task.

Another approach to approximate the effect of postprandial fatigue on individuals' efforts is to compare completion times for test questions and the variability in response times between treatment and control groups. To assess potential variation in test completion times by time of last meal, we regress the completion times of reading in native language, reading in English, math, and oral comprehension questions on the treatment variable. To examine how response consistency differs across treatment status, we also regress the variance of completion times on the treatment variable. The resulting coefficient estimates are reported in Online Appendix A2 and indicate that completion times and the variance of completion times do not significantly change during the postprandial period. This result supports our previous findings that the effect of fatigue on test performance in the postprandial period primarily occurs through a decrease in cognitive capacity rather than a decrease in motivation. We however acknowledge that completion times for test questions and the variability in response times are not perfect indicators of motivation, but they are the best available proxies in our sample. We leave the deeper investigation of the effect of the postprandial period on motivation for future research.

4.4 Heterogeneity analysis

In this section, we explore heterogeneity in the effects of post-meal testing along several dimensions. First, the effect of post-meal testing may 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 natural sleepy phase in humans' circadian rhythms regardless of meal times. 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 7, Panels A, B and C respectively show the estimates in the samples of respondents who test in the morning (8am-1pm), at lunchtime/afternoon (1pm-5pm) and the evening (after 5pm). The negative effects of post-meal testing on cognitive abilities do not seem 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 post-meal effects might exist at other times. Hence, in addition to the circadian cycle-based explanation of the postprandial dip, other factors linked to the digestive process itself might impact cognitive alertness. Furthermore, our confirmation of a detrimental effect of postprandial testing at various times of the day helps alleviate concerns that the identified effects may be attributed to enumerator fatigue.

Second, we examine how the effects of post-meal testing may vary by socioeconomic status (SES). Research has shown that the effects of the postprandial dip worsen 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 SES (Backholer et al., 2016; Michels et al., 2018; Vos et al., 2022). We test the hypothesis that a decline in meal quality exacerbates the negative effects of the postprandial dip by re-estimating equation

[11] The p-values in the bottom of Table 7 suggest no differences in the effects of post-meal testing performances between the morning and the evening.

(1), stratifying the sample by dividing it into terciles of SES. In Table 8, Panels A, B and C respectively contain coefficient estimates for 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$<$0.01 for four out of five outcomes). Specifically, there is suggestive evidence of a SES gradient in the impact of food coma on performance in reading in native language, reading in English, mathematics, and Raven's scores in Columns (1) to (4) – the treatment gaps in cognitive skills are 0.08, 0.07, 0.12 and 0.28 standard deviations in SES tercile 1 and some of them more than double to 0.45, 0.38, 0.34 and 0.55 in SES tercile 3. By contrast, the non-monotonicity of the coefficient-estimates' 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 finding may occur because individuals in wealthier households can afford to consume higher quantities of carbohydrates than poorer respondents. Another explanation could be that individuals' nutrition in the first tercile is so poor that the marginal effect of postprandial testing is insignificant compared to the highly detrimental state of their overall nutrition. This explanation aligns with the significant disparity in wealth observed between households in the first and third terciles of the asset index. To highlight this distinction, let's consider the qualitative evaluation of the 24 items (e.g., chair, bed, table, TV) used to create the asset index as a representation of SES. Within the lowest wealth tercile, households have possession of merely 5 of these items, whereas within the highest wealth tercile, households own 11 of these items.

Third, we examine whether post-meal testing impacts males and females differently. These results are presented in Table 9 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.

Fourth, because adolescence is associated with specific changes in circadian rhythms (Hagenauer et al., 2009; Yip et al., 2022; Sadeh et al., 2009), 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 10. 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 significantly differ across age categories (the coefficients' differences between Panels A and C are not statistically significant). By contrast, the effects of post-meal testing on Raven's scores and oral comprehension 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 the detrimental effects of post-meal fatigue on respondents' performance on math and oral comprehension tests are particularly pronounced among early adolescents, and tend to diminish with age. Yet more research is needed to corroborate these results. Confirming such a result would have important policy implications. Since early 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 during this period of development would further support advocating for the implementation of naps in elementary and middle school.

5 Robustness tests

5.1 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). Thus, 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 A3. We find that the effect of postprandial testing on cognitive test scores remains negative and statistically significant at the one percent level in six out of seven columns, but the sizes of the estimated coefficients on the treatment dummy are consistently lower across all measures of cognitive attainment. This finding implies that most of the effects of the postprandial dip are concentrated in the hour following meals and that the effects diminish as the times of the tests move away from the times of the last meals.

5.2 Alternative sample

Because we are using endline-survey data from an experiment that could impact respondents' cognitive scores, we test the robustness of our results by restricting our analysis sample to the control villages – where there is no exposure to the intervention or evidence of treatment spillovers. These estimates are reported Table A4. The interpretation of our main findings remains unchanged in this alternative sample.

6 Conclusion

This study identifies the causal effects of post-meal testing on cognitive performance. Using plausibly 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 meal. The impact of food coma is significant and sizable, and found across all measures of language, mathematics, fluid intelligence, and oral comprehension tests. Our analysis further suggests that these effects work through fatigue and decreased cognitive capacities — respondents report being more tired after their last meal and have a harder time completing more complex tasks.

Our results have a few important implications. First, our research findings suggest that for achieving greater comparability in testing conditions, knowledge on the effects of postprandial fatigue should be made salient to *all* test-takers. For example, students should be discouraged from eating big meals before high-stakes tests (such as, GRE or SAT) in order to minimize the effects of food coma on cognitive performance. In the absence of equitable knowledge about food coma, students from high-SES backgrounds are likely to incorporate behavioral responses such as, having a cup of coffee or choosing small meals over larger meals to minimize the effects of food coma on high-stakes tests, whereas students from low-SES backgrounds are likely to take these tests without such behavioral responses, thus magnifying the class- and race-based gaps in test scores found in these settings. Moreover, our findings suggest that standardized tests like PISA, ASER, or any test administered independently by educational institutions should acknowledge the impact of food-related fatigue and strive to establish a fair and unbiased testing environment. One practical step could entail reminding students to refrain from consuming heavy meals prior to exams to minimize the onset of food coma.

Second, our results show that performance on standardized tests do not always reflect student comprehension (Wise and DeMars, 2005; Finn, 2015; Gneezy et al., 2019). In fact, we find that cognitive fatigue severely limits individuals' capacities to perform on low-stakes tests, which suggests potentially important effects on high-stakes tests. More research is thus needed to better understand the causes of cognitive fatigue in order 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; Bradley and Green, 2020). Such policies are already used in China, where naps are common practice for students in schools. Additionally, the results from this study can inform choices on how to optimally structure school days. For instance, Spain was recently debating whether to elect continuous versus split school days. Our findings suggest that split days might help students recover from the fatigue induced by the postprandial period.

A few caveats remain. First, an interesting extension to this paper would be to assess whether, in addition to deteriorating students' performance on tests, post-meal fatigue also damages students' learning generally. Additionally, it would be useful to examine if these findings replicate in other countries and age groups. Lastly, since this paper is the first study to measure the impacts of food coma, more research is needed to determine whether food coma would impact performance in other high-stake settings, such as, SAT testing, job interviews, and the workplace.

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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	
Reading score in native language	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)
Reading score in English	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's matrices test score	Total number of correct responses on the 10-item Raven's test
Oral comprehension score	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

Table 1 – continued from previous page

Variable name	Definitions
Panel C: Testing conditions and chronic issues	
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
Panel D: Background characteristics	
Age	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
Hindu	=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
Mother's age	Mother's age in years
Mother's schooling	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 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	2.37
	(1.257)
Treatment	0.32
	(0.467)
Panel B: Cognitive skills	
Reading score in native language	3.30
	(1.005)
Reading score in English	3.72
	(1.385)
Math score	3.08
	(1.004)
Raven's score	6.23
	(2.685)
Oral comprehension score	1.98
	(0.763)
Panel C: Testing conditions	
Time of test	14.14
	(2.565)
Wake time	6.16
	(1.026)
Fatigue	2.45
	(0.847)
Panel D: Background characteristics	
Age	16.41
	(2.371)
Male	0.57
	(0.496)
Enrolled in school	0.93
	(0.251)
Completed grades of schooling	5.21
	(2.133)
Scheduled Caste	0.23
	(0.419)
Scheduled tribe	0.11
	(0.319)
Other Backward Caste	0.61
	(0.487)

Table 2 – continued from previous page

Variable	Mean (sd)
Hindu	0.87 (0.335)
Salaried	0.46 (0.498)
Below Poverty Line Card	0.93 (0.259)
MNREGA	0.65 (0.476)
Mother's age	35.11 (5.518)
Mother's schooling	1.87 (3.181)
Household size	5.04 (1.769)
Tercile of asset index	1.99 (0.822)
Drinking water available	0.98 (0.145)
Lighting available	1.00 (0.0417)
Cooking fuel available	0.34 (0.473)
Toilets available	0.27 (0.446)
Grandparents in HH	0.09 (0.289)
Observations	4,601

Table 3: Balance checks

	Mean Treatment (1)	Mean Control (2)	Difference (standard error) (3)
Age	15.99	16.60	-0.389***
	(2.408)	(2.328)	(0.073)
Sharpened q-values			[0.001]
Male	0.55	0.57	-0.030*
	(0.497)	(0.495)	(0.016)
Sharpened q-values			[>0.1]
Enrolled in school	0.94	0.93	-0.000
	(0.241)	(0.256)	(0.008)
Sharpened q-values			[>0.1]
Completed grades of schooling	5.25	5.18	-0.101
	(2.121)	(2.139)	(0.068)
Sharpened q-values			[>0.1]
Scheduled Caste	0.22	0.23	-0.031**
	(0.418)	(0.419)	(0.013)
Sharpened q-values			[>0.1]
Scheduled tribe	0.07	0.14	0.003
	(0.257)	(0.342)	(0.007)
Sharpened q-values			[>0.1]
Other Backward Caste	0.64	0.60	0.023
	(0.479)	(0.491)	(0.014)
Sharpened q-values			[>0.1]
Hindu	0.86	0.88	0.012
	(0.349)	(0.328)	(0.010)
Sharpened q-values			[>0.1]
Salaried	0.42	0.47	-0.037**
	(0.494)	(0.499)	(0.015)
Sharpened q-values			[>0.1]
Below Poverty Line Card	0.96	0.91	-0.009
	(0.204)	(0.280)	(0.007)
Sharpened q-values			[>0.1]
MNREGA	0.71	0.63	-0.006
	(0.453)	(0.484)	(0.012)
Sharpened q-values			[>0.1]
Mother's age	34.84	35.24	-0.194
	(5.317)	(5.607)	(0.174)
Sharpened q-values			[>0.1]
Mother's schooling	1.76	1.92	-0.014
	(3.116)	(3.211)	(0.095)
Sharpened q-values			[>0.1]
Household size	5.00	5.06	0.056

Table 3 – continued from previous page

Normalized difference	Mean Treatment (1)	Mean Control (2)	Difference (standard error) (3)
	(1.740)	(1.782)	(0.055)
Sharpened q-values			[>0.1]
Tercile of asset index	2.01	1.98	-0.009
	(0.807)	(0.829)	(0.024)
Sharpened q-values			[>0.1]
Drinking water available	0.99	0.98	0.008**
	(0.121)	(0.155)	(0.004)
Sharpened q-values			[>0.1]
Lighting available	1.00	1.00	-0.001
	(0.0451)	(0.0400)	(0.001)
Sharpened q-values			[>0.1]
Cooking fuel available	0.37	0.32	-0.007
	(0.482)	(0.468)	(0.013)
Sharpened q-values			[>0.1]
Toilets available	0.27	0.27	0.007
	(0.444)	(0.447)	(0.012)
Sharpened q-values			[>0.1]
Grandparents in HH	0.08	0.10	-0.002
	(0.275)	(0.295)	(0.009)
Sharpened q-values			[>0.1]
Observations	1476	3125	

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. *** 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	-0.271***	-0.210***	-0.253***	-0.425***	-0.146***
	(0.030)	(0.029)	(0.032)	(0.033)	(0.032)
Sharpened q-values	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Control mean	3.424	3.825	3.155	6.649	2.021
Observations	4,601	4,601	4,601	4,601	4,601
R-squared	0.278	0.273	0.201	0.241	0.170
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

	Fatigue (1)
Treatment	0.394***
	(0.025)
Sharpened q-value	[0.001]
Control mean	2.300
Observations	4,601
R-squared	0.233
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 includes covariates and fixed effects used to produce Table 4. The self-reported measure of fatigue is described in Panel C of Table 1. *** 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 (1)	Can read sentence (2)	Can read word (3)	Can read letter (4)
Treatment	-0.175***	-0.074***	-0.036***	-0.007*
	(0.014)	(0.012)	(0.008)	(0.004)
Control mean	0.676	0.823	0.938	0.986
Observations	4,601	4,601	4,601	4,601
R-squared	0.296	0.231	0.114	0.0700
Wald-tests' p-value (Can read paragraph=Can read letter) <0.01				
Panel B: Reading in English				
	Can read paragraph (1)	Can read sentence (2)	Can read word (3)	Can read letter (4)
Treatment	-0.128***	-0.125***	-0.064***	-0.008
	(0.015)	(0.014)	(0.012)	(0.005)
Control mean	0.460	0.664	0.828	0.974
Observations	4,601	4,601	4,601	4,601
R-squared	0.258	0.261	0.173	0.0894
Wald-tests' p-value (Can read paragraph=Can read letter) <0.01				
Panel C: Math				
	Can divide (1)	Can substract (2)	Recognize numbers 10-99 (3)	Recognize numbers 1-9 (4)
Treatment	-0.097***	-0.050***	-0.077***	-0.010**
	(0.015)	(0.013)	(0.009)	(0.005)
Control mean	0.459	0.770	0.944	0.980
Observations	4,601	4,601	4,601	4,601
R-squared	0.186	0.187	0.0983	0.0521
Wald-tests' p-value (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 obtained from regressions of different outcomes (listed in Columns 1-4) on the treatment dummy, and includes selected covariates and sets of fixed effects 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). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 7: 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	-0.285***	-0.188***	-0.208***	-0.324***	-0.112**
	(0.045)	(0.043)	(0.048)	(0.048)	(0.047)
Observations	1,921	1,921	1,921	1,921	1,921
R-squared	0.323	0.272	0.239	0.255	0.191
Panel B: Afternoon					
Treatment	-0.297***	-0.287***	-0.261***	-0.553***	-0.125**
	(0.054)	(0.051)	(0.056)	(0.057)	(0.057)
Observations	1,805	1,805	1,805	1,805	1,805
R-squared	0.260	0.275	0.211	0.272	0.192
Panel C: Evening					
Treatment	-0.281***	-0.242***	-0.286***	-0.575***	-0.203***
	(0.080)	(0.076)	(0.087)	(0.086)	(0.077)
Observations	826	826	826	826	826
R-squared	0.370	0.431	0.349	0.367	0.341
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	0.88	0.11	0.26	<0.01	0.69
Morning=Evening	0.75	0.47	0.11	0.02	0.28

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. *** p<0.01, ** p<0.05, * p<0.10.

Table 8: 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	-0.082	-0.070	-0.129**	-0.284***	-0.292***
	(0.061)	(0.058)	(0.061)	(0.057)	(0.062)
Observations	1,585	1,585	1,585	1,585	1,585
R-squared	0.266	0.255	0.205	0.244	0.166
Panel B: SES Tercile 2					
Treatment	-0.345***	-0.245***	-0.256***	-0.439***	-0.067
	(0.053)	(0.049)	(0.056)	(0.058)	(0.056)
Observations	1,492	1,492	1,492	1,492	1,492
R-squared	0.305	0.298	0.231	0.273	0.255
Panel C: SES Tercile 3					
Treatment	-0.453***	-0.382***	-0.345***	-0.553***	-0.104**
	(0.047)	(0.044)	(0.054)	(0.057)	(0.049)
Observations	1,521	1,521	1,521	1,521	1,521
R-squared	0.341	0.344	0.286	0.335	0.245
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	0.03	0.04	0.03
SES Tercile 1=SES Tercile 3	<0.01	<0.01	<0.01	<0.01	0.22

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 final rows reports the p-values corresponding to the coefficient on 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 9: 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	-0.364***	-0.267***	-0.266***	-0.494***	-0.207***
	(0.048)	(0.045)	(0.050)	(0.050)	(0.049)
Observations	2,000	2,000	2,000	2,000	2,000
R-squared	0.313	0.312	0.239	0.261	0.215
Panel B: Male					
Treatment	-0.240***	-0.203***	-0.225***	-0.407***	-0.111***
	(0.040)	(0.038)	(0.043)	(0.044)	(0.042)
Observations	2,599	2,599	2,599	2,599	2,599
R-squared	0.264	0.265	0.201	0.246	0.175
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	0.05	0.27	0.34	0.35	0.23

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 final row contains the p-values corresponding to the coefficient on the interaction between the treatment and the male dummy 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 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	-0.295***	-0.280***	-0.422***	-0.523***	-0.481***
	(0.068)	(0.057)	(0.071)	(0.067)	(0.068)
Observations	1,000	1,000	1,000	1,000	1,000
R-squared	0.369	0.353	0.303	0.308	0.312
Panel B: Middle-adolescence					
Treatment	-0.274***	-0.177***	-0.185***	-0.409***	-0.066
	(0.046)	(0.044)	(0.049)	(0.049)	(0.048)
Observations	2,176	2,176	2,176	2,176	2,176
R-squared	0.246	0.250	0.204	0.220	0.185
Panel C: Young adults					
Treatment	-0.273***	-0.224***	-0.164***	-0.425***	0.059
	(0.053)	(0.055)	(0.056)	(0.061)	(0.054)
Observations	1,404	1,404	1,404	1,404	1,404
R-squared	0.244	0.300	0.269	0.251	0.225
Controls	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes
Coefficients' p-values from treatment*male interaction					
Early adolescence=Middle adolescence	0.15	0.07	<0.01	0.12	<0.01
Early adolescence=Young adults	0.27	0.16	<0.01	0.41	<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. *** p<0.01, ** p<0.05, * p<0.10.

Online Appendix

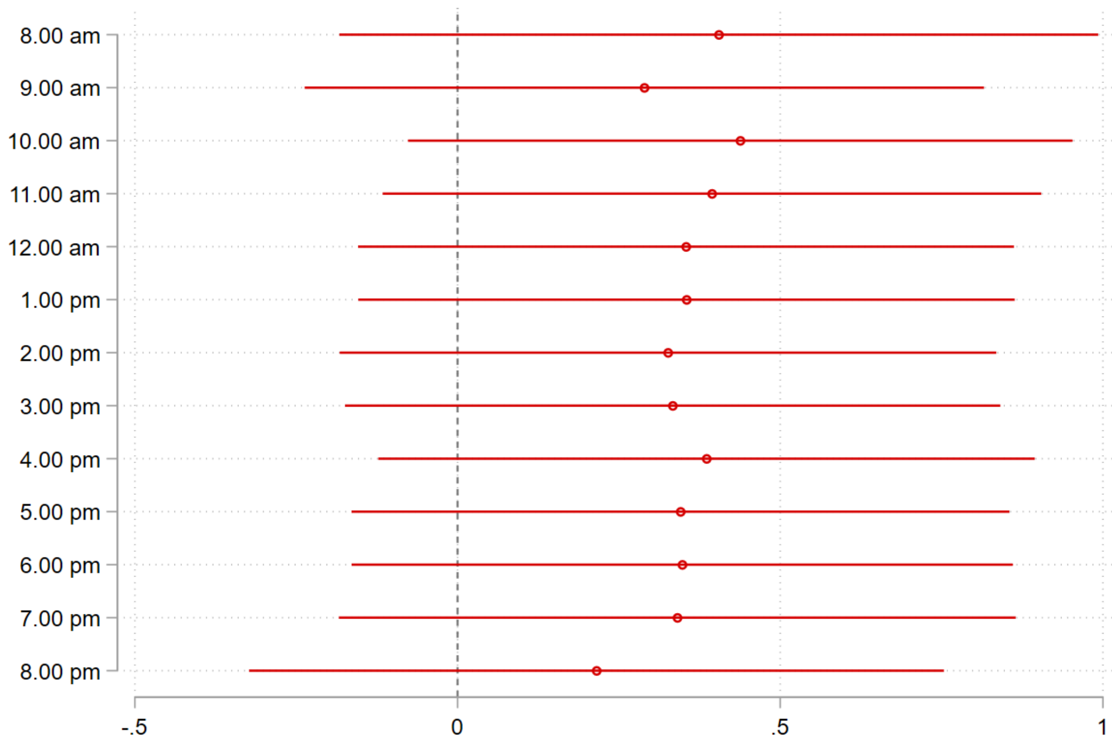

Figure A1: Coefficient estimates from the regression of SES on time dummies

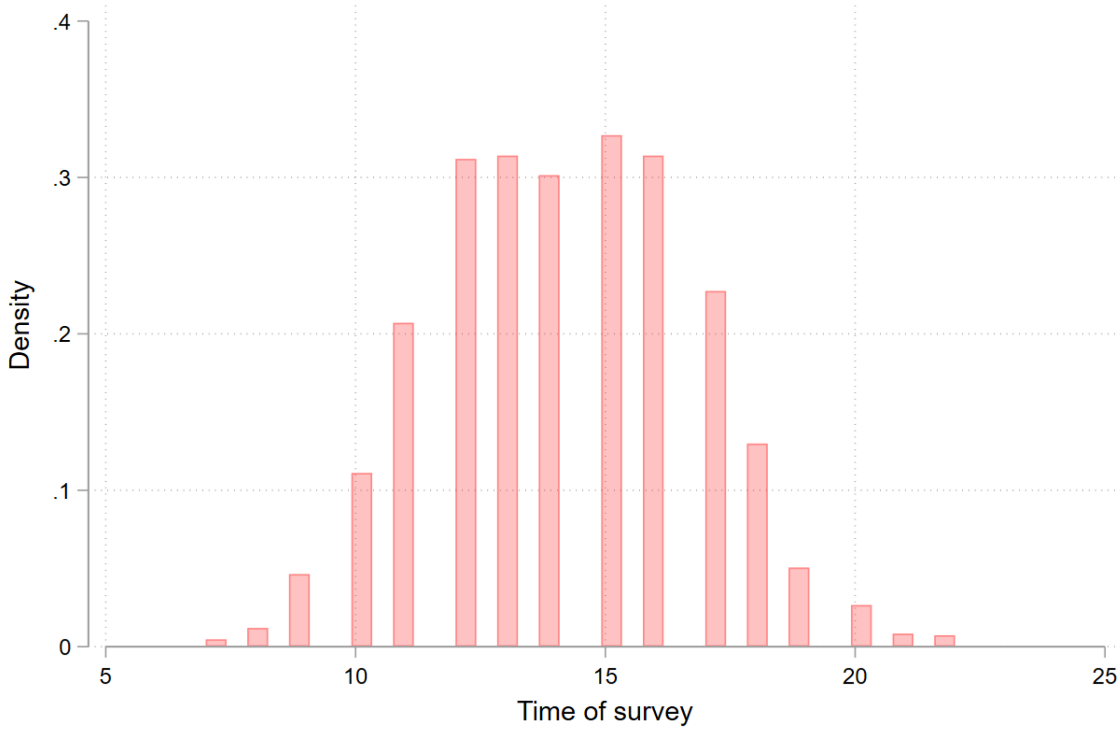

Figure A2: Distribution of survey times

Table A1: Regression of survey times on background characteristics

	Survey time
Age	-0.088***
	(0.023)
Male	-0.033
	(0.073)
Enrolled in school	-0.073
	(0.166)
Completed grades of schooling	0.023
	(0.024)
Scheduled Caste	0.081
	(0.197)
Scheduled Tribe	-0.020
	(0.259)
Other Backward Caste	-0.057
	(0.185)
Hindu	0.176
	(0.118)
Salaried	0.121
	(0.080)
Below Poverty Line Card	-0.194
	(0.173)
MNREGA	0.067
	(0.102)
Mother's age	0.027***
	(0.007)
Mother's schooling	0.016
	(0.013)
Household size	0.040*
	(0.024)
Tercile of asset index	-0.062
	(0.054)
Drinking water available	-0.226
	(0.309)
Lighting available	0.002
	(0.871)
Cooking fuel available	0.063
	(0.105)
Toilets available	0.001
	(0.108)
Grandparents in HH	-0.136
	(0.140)

Table A1 – continued from previous page	
Observations	4,601
R-squared	0.143
Controls	Yes
Village FE	Yes
Age-group FE	Yes

Notes: This table presents the coefficient estimates obtained from regressions of the time of test on the background characteristics presented in panel D of Table 1 and village and age-group fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Effect of post-meal testing on question completion times and variance of completion times

	Reading in native language	Reading in English	Math	Oral comprehension	Completion time variance
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.549	0.067*	0.670	0.012	-11.826
	(1.186)	(0.037)	(0.622)	(0.026)	(179.507)
Observations	4,601	4,601	4,601	4,601	4,601
R-squared	0.026	0.131	0.0280	0.166	0.0319
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 completion time and variance of completion times' outcomes on the treatment dummy, selected covariates and sets of fixed effects, similar to those used to produce Table 4. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A3: 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	Can read paragraph	Fatigue
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.267***	-0.175***	-0.221***	-0.363***	-0.051*	-0.139***	0.278***
	(0.029)	(0.027)	(0.031)	(0.031)	(0.030)	(0.013)	(0.024)
Observations	4,601	4,601	4,601	4,601	4,601	4,601	4,601
R-squared	0.269	0.266	0.199	0.225	0.165	0.289	0.212
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	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 their last meal happened more than two hours before they were interviewed. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: 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	Can read paragraph	Fatigue
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.177***	-0.152***	-0.155**	-0.230***	-0.248***	-0.099***	0.364***
	(0.057)	(0.056)	(0.060)	(0.059)	(0.060)	(0.025)	(0.045)
Observations	1,444	1,444	1,444	1,444	1,444	1,444	1,444
R-squared	0.307	0.202	0.202	0.225	0.257	0.374	0.326
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-group FE	Yes	Yes	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. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.