Journal of Development Economics 179 (2026) 103613

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Regular Article

The effects of nutrition support on behavioral outcomes and labor productivity☆

Seollee Park[a], Hyuncheol Bryant Kim[b,c,*]

[a] School of Economic Sciences, Washington State University, United States of America
[b] Department of Preventive Medicine, College of Medicine, Yonsei University, Republic of Korea
[c] Department of Economics and Division of Public Policy, Hong Kong University of Science and Technology, Hong Kong

ARTICLE INFO

JEL classification:
I15
J24
O12
O15

Keywords:
Nutrition support
Behavioral outcomes
Stress
Prosocial behavior
Productivity
Hedonic adaptation

ABSTRACT

While many of the world's poor consume inadequate calories with low nutritional value, there has been little work on how this may shape their behaviors and productivity. Using lab-in-the-field and field experiments in the context of a floriculture plant in Ethiopia, this study investigates the effects of a nutrition support program on behavioral outcomes—stress, prosociality, cooperation, and attention—and productivity. We find that nutrition support relieves stress and decreases prosociality, exhibiting a pattern of hedonic adaptation over time. We do not find evidence for improvements in labor productivity.

1. Introduction

While many of the world's poor consume inadequate calories with low nutritional value, there has been little work on how this may shape their behaviors. Existing associational studies suggest a potential link between poor nutrition and behavioral outcomes, such as difficulties in emotion regulation, increased costs of cooperation, diminished cognitive function, and impaired attention (Benton and Donohoe, 1999; Danziger et al., 2011; Dean et al., 2018; US Army Institute of Environmental Medicine, 1987). Although some limited laboratory-based research hint at a causal relationship, it is not clear if the results are generalizable in the field (Gilliot et al., 2007).

Recent studies have primarily focused on the causal impact of *poverty* on behavioral and mental outcomes, which subsequently affect economic outcomes such as productivity and labor supply (Haushofer and Fehr, 2014; Ridley et al., 2020; Schilbach et al., 2016). However, there remains a significant gap in understanding the underlying mechanisms through which poverty affects behavioral and mental outcomes. This paper aims to address this gap by specifically investigating the direct and causal impact of nutrition, a prevalent deprivation associated with poverty, on behavioral outcomes.

Also, although the positive relationship between nutrition and labor productivity is supported by a longstanding and large theoretical literature on nutrition-based poverty traps (Yellen, 1957; Mazumdar, 1959; Stiglitz, 1974; Reynolds, 1976; Bliss and Stern, 1982; Dasgupta and Ray, 1986, 1987; Dasgupta, 1993), empirical evidence on this link

☆ We wish to thank John Hoddinott, Syngjoo Choi, David Just, Frank Schilbach, Berk Özler, and seminar participants at American Society of Health Economists (ASHEcon) conference, Asia Impact Evaluation Conference, Cornell University, North East University Development Consortium (NEUDC), and Washington State University for their feedback. We also thank Minah Kim, Jieun Kim, Bewuketu Assefa, Banchayew Asres, Betelhem Muleta, Tizita Bayisa, Dechassa Abebe, Hyolim Kang, Jiwon Baek, Tembi Williams, Soo Sun You, Jeong Hyun Oh, Jiyeong Lee, and Yue Yu for their excellent fieldwork and research assistance, and Rahel Getachew, Chulsoo Kim, Hongryang Moon at Myungsung Christian Medical Center for their support. This project was funded by Africa Future Foundation, Korea Foundation for International Healthcare (KOFIH), and Seoul Women 's Hospital. Kim's work was supported by a new faculty research seed money grant of Yonsei University College of Medicine (2024-32-0098), and a faculty research grant of Yonsei University College of Medicine (6-2024-0158). All views expressed are ours, and all errors are our own. The study was approved by ethical review committees at the Oromia Health Bureau (Ethiopia, BEFO/HBTSH/1-8/71), Myungsung Medical College (Ethiopia, MMC/EC/743/2017), and Cornell University (USA, 1711007621). This project is registered with the AEA RCT registry under ID AEARCTR-0002620.

* Corresponding author.
E-mail addresses: seollee.park@wsu.edu (S. Park), hk2405@yuhs.ac (H.B. Kim).

https://doi.org/10.1016/j.jdeveco.2025.103613
Received 22 March 2025; Received in revised form 14 August 2025; Accepted 14 August 2025
Available online 12 September 2025

is sparse and mixed.[1] Moreover, most empirical studies that examine this relationship were conducted at least two decades ago, calling into question the external validity of existing evidence in current times, especially after rapid nutritional change in the past few decades (Black et al., 2013).

In this study, we directly address the limitations of the previous studies. We examine the effect of nutrition on labor productivity and physical function in the context of a floriculture farm in Ethiopia. Specifically, this paper investigates the impacts of a nutrition support program that randomly provides nutritious filling breakfasts of about 500 calories with rich micronutrients to floriculture manual workers for ten weeks. To explain the mechanisms underlying this relationship, we assess the extent to which nutrition affects workers' stress, prosociality, cooperation, and attention.

This study tests the hypothesis that improved nutrition affects productivity not only through physical capacity but also via psychological and behavioral channels. As outlined in Fig. 1, the theory of change posits that increased access to nutrient-rich food can reduce stress and improve prosociality, cooperation, and attention—traits that are relevant for productivity in labor-intensive team environments like floriculture. These behavioral mechanisms are supported by evidence linking nutrition to cognitive and emotional function and social behavior (Benton and Donohoe, 1999; Carvalho et al., 2016; Haushofer and Fehr, 2014). Tasks such as cultivating, harvesting, sorting, and packing roses required sustained attention and team coordination, especially in shared greenhouse and packhouse spaces.

We hypothesize that better-nourished workers may exhibit greater intrinsic motivation, lower stress, or more prosocial conduct, all of which could enhance productivity. Our analysis therefore examines a range of intermediate outcomes, both behavioral and physical, alongside final labor productivity measures. The flower plantation setting is well-suited for this research insofar as it provides a unique opportunity to provide targeted nutrition interventions and measure high-frequency productivity data as well as behavioral outcomes through lab experiments.

As pre-registered in Park and Kim (2017), the behavioral outcomes we examine include: (1) emotional state and stability (stress); (2) prosocial behaviors measured by the dictator game and the ultimatum game for the degree of self-interest and fairness, and the trust game for the degree of trust and reciprocity[2]; (3) workers' level of cooperation measured by performance in the length of time the worker spent on helping other workers during work; and (4) workers' level of attention captured by bean sorting tasks and a search game.[3] Physical function is measured by gross and fine motor tests and body mass index (BMI). For productivity outcomes, we collected the number of flowers each worker harvested, sorted, or bunched per day, and recorded daily attendance as a measure of labor supply.

We find that the nutrition support program enhances workers' dietary intake in terms of both quality (dietary diversity) and quantity (caloric intake). Although partial crowding-out is observed, caloric intake increases by 223 calories, and the consumption of eggs, dairy, and meat and fish increased among the treatment group, suggesting increases in not only caloric intake but also micronutrient consumption.

Regarding behavioral outcomes, we demonstrate that nutrition support reduces stress levels and diminishes prosociality, but has no effect on cooperation and attention. Specifically, stress decreases by 0.23 standard deviations (SDs) among treated workers, reflecting improved emotional state and less emotional fluctuations. Also, the program leads to decreased prosociality by 0.06 SDs, as evidenced by reduced generosity in the dictator and ultimatum game allocations, and less fair offers in the dictator game. Trust levels decrease, with treated workers allocating less, and reciprocity increases, with treated workers reciprocating more in the trust game. We find no effect on cooperation in the lab and evidence for reduced cooperation in the field.

We do not find effects of the nutrition support on physical ability or labor productivity. The null effect on productivity is precise, as this estimate is bounded to a tight interval around zero, suggesting that nutrition may not be the main binding constraint for the average worker on the farm.

Our analysis also reveals evidence for hedonic or behavioral adaptation, in which effects are pronounced in the first several weeks but dissipate over time. Hedonic adaptation is most prominent in the results on emotional state. This trend is also evident across various other outcomes such as prosociality and productivity outcomes, underscoring the importance of considering longer-term impacts of nutrition over time.

This study contributes to the literature on two fronts. First, we document the effect of nutrition on behavioral and psychological outcomes, which is a promising yet less developed area of research in behavioral and development economics. We also add to the growing literature on poverty and mental outcomes, exploring nutrition as a potential underlying mechanism. In this paper, we show that nutrition plays a significant causal role in emotional well-being and prosocial behaviors. To the best of our knowledge, ours is the first to credibly investigate the effects of nutrition on these behavioral outcomes.

Secondly, this study provides causal evidence on the relationship between nutrition and labor productivity. Despite its important economic implications, to the best of our knowledge, no paper has credibly established a causal relationship in the past two decades, during which profound nutritional changes have occurred in the developing world (Headey et al., 2017). This paper addresses this gap with a more rigorous empirical approach by using a randomized control trial to infer causality, taking advantage of the floriculture farm setting to precisely measure labor productivity, and providing adequate nutrition support in terms of both quantity and quality. We find that nutrition support does not improve labor productivity at least in the short term among adults in a manual labor setting.

[1] Most existing empirical studies are associational, given the inherent challenges posed by the endogeneity of caloric intake and the measurement of productivity (Kraut and Muller, 1946; Strauss, 1986; Deolalikar, 1988; Croppenstedt and Muller, 2000; Chakrabarty and Grote, 2009). The few (quasi-)experimental studies that exist, albeit with weaknesses in study design, find mixed results, making it difficult to generalize whether nutrition improves productivity (Immink and Viteri, 1981; Wolgemuth et al., 1982). A recent experimental study by Schofield (2018) provides important evidence by randomly providing 700 calories per day to low-BMI cycle-rickshaw drivers in India for five weeks, finding increased labor supply and income. While this study is rigorously designed, the study has several limitations we seek to address: (1) the study measures labor supply but not productivity, (2) the intervention provided calorie-dense snacks with minimal nutritive value, (3) the study had differential and selective attrition between the treatment and control groups despite small sample size, and (4) the extent of nutritional crowding out is unclear. The literature on religious fasting (Ramadan) suggests reduced output growth and productivity (Campante and Yanagizawa-Drott, 2015; Schofield, 2020). However, using Ramadan fasting as a quasi-experiment to study the relationship between nutrition and productivity has limitations, as fasting coincides with changes in sleep patterns, work hours, and religious practices, making it difficult to isolate the effects of nutrition alone. Lastly, while not in the form of regular meals, Thomas et al. (2006) show that iron supplements improved labor supply and productivity among men, and Hoddinott et al. (2008) find long-term impacts of early childhood nutrition supplements on adult economic productivity.

[2] Prosocial behaviors refer to voluntary actions that may benefit other individuals such as sharing. They include altruism toward others, spite/competitiveness toward others, reciprocity, and fairness. Altruism is a special case of prosociality in which an actor benefits others but at personal cost or helping in the absence of external rewards (Batson and Powell, 2003).

[3] Attention is the ability to focus on particular pieces of information by engaging in a selection process that allows for further processing of incoming stimuli (Dean et al., 2018).

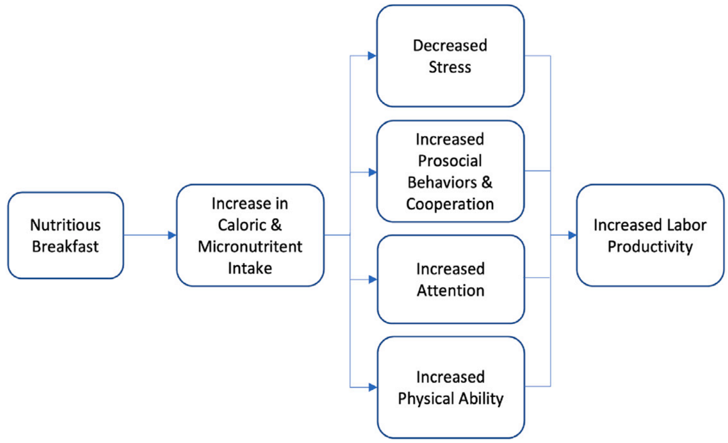

Fig. 1. Theory of change.

The remainder of this paper is organized as follows: Section 2 explains the study design and the intervention; Section 3 discusses data and sample characteristics; Section 4 presents the estimation strategy; and Section 5 presents the results. We conclude in Section 6.

2. Study design and intervention

2.1. Study setting

Ethiopia is one of the least developed countries in the world with a GDP per capita in 2020 of US$936 and is the second most populous country in sub-Saharan Africa (World Bank, 2020). The Ethiopian floriculture industry has expanded considerably in the past decade, making it the second largest flower producer in Africa after Kenya and serving as the fifth foreign revenue earner for the country. The sector predominantly employs female manual laborers in the main production process: farming, packing, and quality control (Woldeyohannes, 2015).

This study includes workers engaged in the farming and packing processes in the floriculture sector. Farming involves seeding, breeding, and raising flowers in greenhouses, with rose buds typically taking two to four weeks to bloom. The packing process, conducted in packhouses, entails sorting and packaging flowers of similar size into bundles (e.g., of 10 pieces). A majority of the packed flowers are shipped for exports to the European and Middle Eastern markets. Workers in this sector typically earn around 30 Ethiopian Birrs per day (equivalent to approximately 1.30 US dollar). As this is significantly less than the average wage in Ethiopia, floriculture farm jobs are often taken up by the poor.

This research was conducted at Ethio AgriCEFT PLC, a rose floriculture farm located in Holeta, approximately 40 km west of Addis Ababa, Ethiopia's capital (Figure A1). A typical worker in this farm works eight-hour shifts from 7 am to 4 pm with a lunch break in between (Panel B of Fig. 2). The farm employs about 270 greenhouse workers across 23 greenhouses, with each worker is responsible for tending to around 21 beds of roses. They engage in a variety of cultivation practices including bending, disbudding, pinching, and harvesting (Figure A2). Each worker within a greenhouse is assigned the same cultivation practice in a given day. Their daily productivity is primarily measured by the number of roses harvested, which can be considered as the final measure of output as it represents successful cultivation practices.

As for the packhouse, there are about 70 workers who are divided into sorters and bunchers. Productivity is measured by the number of rose stems bunched by a pair of one sorter and one buncher. The pair's target is to sort and bunch 3000 stems of roses per day, and for any work above the target, the team receives 25 Ethiopian cents per 10 stems as incentives. The incentives are evenly split between the sorter and the buncher. Team assignment changes every day at the discretion of the supervisor.

The farm's production fluctuates throughout the year, depending on overseas demand. January and February are typically peak seasons driven by holidays and Valentine's Day demands, whereas July through September and November are the low seasons due to local weather conditions (rainy season with lower temperatures).[4] To ensure high effort levels from workers, the study was implemented during the busiest production season, from December 2017 to March 2018. This timing aimed to minimize any potential impact of seasonal production variations on worker performance.

2.2. Experimental design and intervention

All workers involved in the main production processes of farming and packing agreed to participate in the study. They were then randomly assigned to the treatment or the control group at the individual level, stratified by greenhouse and packhouse.[5] Among a total of 347 workers, 173 workers were assigned to the treatment group and the remaining 174 workers to the control group. Individual workers were informed of their treatment status by their respective greenhouse and packhouse supervisors.

As shown in Panel A of Fig. 2, the treatment group received daily nutritious breakfasts with adequate macro and micronutrients for ten weeks from December 2017 to February 2018.[6] This breakfast, provided on weekdays, comprised a balanced mix of staple foods, protein supplements from animal source foods or beans, vitamin and mineral supplements from fruits or vegetables, and energy supplements to

[4] However, even during low seasons, farm managers reported that there are sufficient number of stems to farm, cut, sort, and pack in a given day, and that there is no stock-out risk. Also, there are no layoffs or additional employment to meet the production drops or spikes—all farm workers are permanently employed.

[5] Among a total of 554 workers in this farm, workers in the farming and the packing process were invited to participate in this study. Workers outside the farming and packing process such as administrative workers and cleaners were excluded.

[6] We provided breakfast because, through focus group discussions and pilot feedback, workers reported that they generally feel hungriest from 9 am to just before lunch, which is plausible given that they reported generally skipping breakfast before coming to work. This implies that many workers experience more than 15 h of prolonged fasting almost every day, which lasts from the previous evening's dinner until the next day's lunch. Our baseline data confirms this, showing that 51% of the sample reported not having breakfast before coming to work.

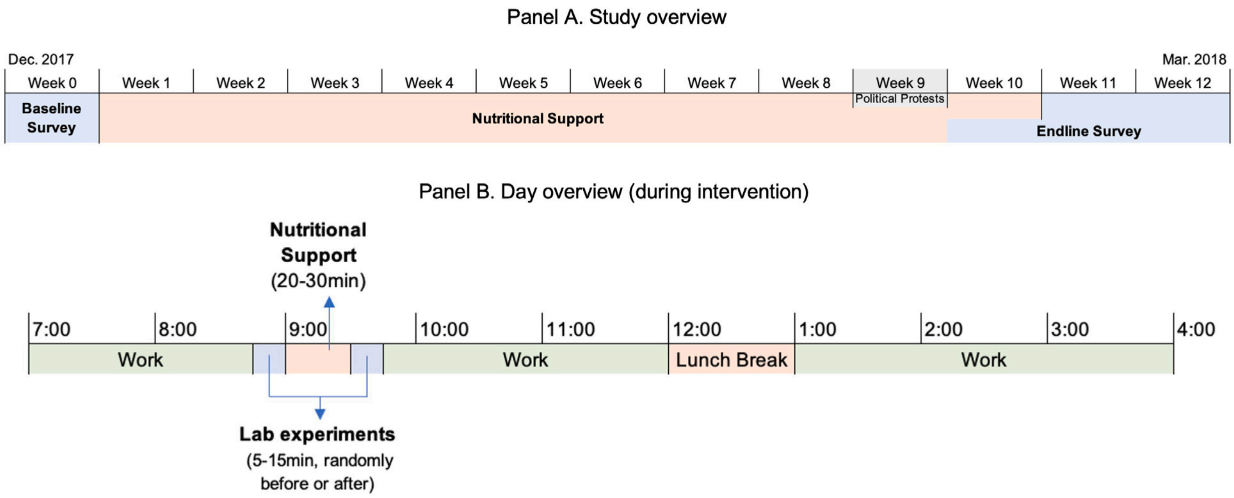

Fig. 2. Study timeline.
Notes: This figure shows study timeline overview (Panel A) and study schedule in a given workday (Panel B). On each day from week 1 to week 10, workers in both the control and treatment groups participated in the lab experiments either just before or after eating the breakfast (assigned randomly), and the lab experiment lasted 5–15 min per person depending on the exercise. Breakfast time lasted about 20–30 min per person, after which they returned to work. Lab experiments were not conducted in week 9 due to political protests in the area, but the nutritional support was continued during this time. Days in weeks 11 and 12 were similar to Panel B, except that the nutritional support was replaced by small snacks.

increase energy density (Figure A3). Each meal contained approximately 500 calories per person. The breakfast content and schedule are provided in Figure A4.[7]

During the same period, the control group received snacks with little nutritional value (around 80 calories with limited micronutrients) (Figure A3). To rule out the effect of taking a break while eating the snacks, the control group also received a snack break time at the same time the treatment group received breakfasts. To prevent any bias from the fairness issue, control group workers were informed at the outset of the study that they would receive a food voucher worth approximately 10 US dollars upon completion of the intervention.[8] Both breakfasts and snacks were provided in respective designated areas, with separate eating spaces for the treatment and the control groups far apart from each other to minimize the salience of the treatment and to avoid any interaction between the two groups while eating.

The breakfasts for the treatment group and the snacks for the control group were distributed around 9 am (Panel B of Fig. 2). Breakfast is the most suitable meal to offer as many workers skip breakfast, and thus, have been fasting since the previous day's dinner. The distribution time was set late enough to cover all late workers, but early enough to prevent crowding-out at lunch. To ensure take-up, all food was prepared by a local restaurant following local recipes. Each participant spent approximately 20 to 30 min to eat the breakfast/snack. All participants consumed the full amount distributed at the designated area before returning to work. There were no leftovers to share with others or take home.

It is worth noting that the way in which the nutrition support program is delivered may generate ancillary effects. For example, workers in the treatment group may experience greater camaraderie from eating together or feel more valued by the employer, potentially reducing stress or changing behavior independent of the additional calories or nutrients consumed. While we cannot fully isolate the nutritional mechanism from these social mechanisms, we aimed to minimize such concerns by ensuring that both treatment and control groups eat in similar social settings.

3. Data

3.1. Data sources

Our primary data sources are: (1) baseline and follow-up surveys, (2) lab-in-the-field experiment data measuring behavioral outcomes, and (3) farm administrative data including daily productivity and attendance records.

The baseline survey collected a wide range of information, including demographic and socioeconomic background, nutrition and health-related variables, as well as assessments of motor skills, anthropometry, economic decision-making, and cognitive skills. A similar endline survey was administered at the end of the intervention period.

To measure behavioral outcomes, we conducted lab-in-the-field experiments. The behavioral lab experiment schedule, detailed in Figure A5, involved multiple rounds of data collection, including baseline and endline surveys, with some behavioral outcomes assessed weekly to capture temporal dynamics of the treatment effect (Fig. 2). The behavioral outcomes collected weekly are: (1) stress measured by the positive and negative affect score; (2) prosocial outcomes from dictator, ultimatum and trust games; (3) cooperation outcomes using the partner sorting game and search game; (4) attention measured by individual sorting game.[9] Weekly games or tasks were scheduled on varying days of the week to mitigate potential day-specific effects.

In addition, farm administrative data provided information on individual worker performance on a daily basis, collected through greenhouse and packhouse supervisors. In particular, they recorded the

[7] With the vast majority of the sample being Orthodox Christians, the breakfast schedule followed the regular fasting schedules of Orthodox Christians, providing only vegetarian food on all Wednesdays and Fridays, and both vegetarian and non-vegetarian options during the Christmas and Easter fasting seasons.

[8] The compensation offered to the control group amounted to 28% of the additional value of the breakfast provided to the treatment group. Although study budget constraints prevented us from matching the treatment value, the 10 USD transfer to control workers was still substantial—equivalent to approximately 9 days of wages. Moreover, the treatment was blinded, making it difficult for control group workers to accurately estimate the value of the nutrition support.

[9] Lab experiments were not conducted in week 9 of the intervention due to political protests nearby the study site.

Table 1
Summary of main outcomes.

Outcome category		Outcomes measured	Frequency
First stage outcomes			
Nutrition	24-hour dietary recall	- Caloric intake and dietary diversity from 24-h dietary recall	Baseline
	Household food consumption	- Household dietary diversity score	Endline
		- Household food expenditures	
Behavioral outcomes			
Stress	Emotional state	- Positive, and negative affect scores from the positive and negative Affect schedule	Weekly
	Emotional stability	- Changes over time in the above scores	
Prosocial behaviors	Dictator Game	- Amount shared and whether fair offer in DG as measures of generosity and fairness	Weekly
	Ultimatum Game	- Amount shared, whether fair offer, and whether rejected offer in UG	
	Trust Game	- Amount shared to recipient as a measure of trust	Weekly
		- Amount shared back to allocator as a measure of reciprocity	
Cooperation	Team sorting game	- Time taken	Weekly
		- Number of errors	
	Help given time	- Number of minutes spent on helping other's tasks in the workplace.	Daily
	Inter-colleague Cooperation	- Assessment received by other colleagues working in the same greenhouse/packhouse on how cooperative the worker is in the workplace	Baseline Endline
Attention	Individual sorting game	- Time taken	Weekly
		- Number of errors	
	Search game	- Time taken	Baseline
		- Number of errors	Endline
Physical function and productivity outcomes			
Physical function	Motor function	- Gross motor skills	Baseline
		- Fine motor skills	Endline
	Anthropometry	- Body mass index (BMI)	Baseline Endline
Labor productivity	Attendance	- Daily attendance	Daily
	Productivity measures by positions	- Greenhouse workers: Number of flowers harvested	Daily
		- Packhouse workers: Number of flower stems sorted/bunched	

number of flowers each worker harvested, sorted, or bunched per day, as well as measures of cooperation with other workers. Attendance records and information on breakfast consumption were also collected.

3.2. Outcome variables

Table 1 summarizes the nutritional, behavioral, and productivity outcomes and their respective data collection frequencies, and Appendix B provides a detailed description of the behavioral outcomes measurement.

To evaluate the impact of our intervention on total nutritional intake, we collected several outcomes related to nutrition. First, we conducted the 24-h dietary recall to analyze overall caloric intake and dietary diversity at baseline before the intervention and on the last week of the intervention.[10] We also collected household-level food consumption and expenditure information to calculate household dietary diversity score (HDDS)[11] and weekly household food expenditure.

Within each domain of behavioral outcomes, we have several outcome measures. To measure stress or emotional state, we used the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) which is widely used in the psychological and behavioral economics literature to assess emotional state. We also examine change rates in PANAS to examine emotional fluctuations.

As a measure of prosocial behaviors, we employed the Dictator Game (DG) and the Ultimatum Game (UG) to measure fairness and generosity, and the Trust Game (TG) to measure the degree of trust and reciprocity. All DG, UG, and TG involved an allocator and a receiver, in which the allocator was asked to allocate 100 birr between herself (allocator) and the other worker (receiver). Both workers learned about their outcomes after the allocator made the decision.

In the DG, the allocator could freely allocate 100 birr between herself and the receiver, and the receiver had no choice but to accept the allocated amount (Forsythe et al., 1994). The outcomes measured in this game are: (1) the amount allocator shared with the receiver and (2) whether the shared amount was fair (50 or more). In the UG, when the allocator makes the offer, the receiver could accept or reject the offer. If the offer is accepted, the offer would take place as proposed, but if rejected, both would earn nothing (Güth et al., 1982). The outcomes measured in this game are: (1) the amount allocator shared with the receiver, (2) whether the shared amount was fair (50 or more), and (3) whether the receiver rejected the offer. In the TG, the amount offered to the receiver was tripled, while the amount the allocator kept retained the same value. After receiving the tripled amount, the receiver could give some amount back to the allocator (Berg et al., 1995). The outcomes measured in this game are: (1) the amount allocator shared with the receiver as a measure of trust, (2) whether the shared amount was fair (50 or more), and (3) the proportion of the tripled amount reciprocated as a measure of reciprocity.

[10] We calculate the dietary diversity score (DDS) following the definition for women's dietary diversity score which is based on the consumption of the following ten food groups: (1) Grains, roots, and tubers; (2) Pulses; (3) Nuts and seeds; (4) Dairy; (5) Meat, poultry, and fish; (6) Eggs; (7) Dark leafy greens and vegetables; (8) Other vitamin A-rich fruits and vegetables; (9) other vegetables; and (10) other fruits (FAO and FHI 360, 2016). Minimum dietary diversity (MDD), following the definition for minimum dietary diversity for women, measures whether at least five out of ten food groups were eaten in the past 24 h, predicting micronutrient adequacy. While originally validated for women, these measures can be used to assess dietary diversity in men, given the lack of a validated metric for men. Studies have shown that the DDS and MDD for women performs well in predicting micronutrient adequacy in men as well (Gómez et al., 2024; Marla and Padmaja, 2023; Singh et al., 2020).

[11] The HDDS is the number of food groups consumed by a household over the past week out of the following 12 food groups: (1) cereals, (2) roots and tubers, (3) vegetables, (4) fruits, (5) meat and poultry, (6) eggs, (7) fish and seafood, (8) pulses, legumes, and nuts, (9) milk and milk products, (10) oils and fats, (11) sugar and honey, and (12) spices and condiments.

The allocator and receiver pairs were assigned randomly in all games each time the games were conducted. The games were conducted weekly on different days of the week. A limitation is that these questions were asked hypothetically and not incentivized, introducing the possibility of hypothetical bias. While some studies find no significant bias in mean responses (Camerer and Hogarth, 1999; Mentzakis and Mestelman, 2013), a meta-analysis of dictator games finds that hypothetical games lead to slightly higher allocations, though the differences are modest and hypothetical responses remain a reasonable proxy for actual behavior (Engel, 2011).

Also, to measure workers' cooperation, greenhouse supervisors recorded the length of time each worker spent in helping other workers during work. Inter-colleague assessment of other workers' cooperation levels was also administered at baseline and twice at follow-up.

Attention span was measured using standardized tasks employed in the economics and psychology literature such as a variant of the Concentration Endurance Test which allowed for estimating individual attention and concentration performance (Bates and Lemay, 2004; Grant and Berg, 1948). Tailoring the game to the field context, the game involved sorting a bowl of beans into sets of 10. This task is similar to the sorting and bunching task of flowers at work that require close attention. In addition, a search game was administered at baseline and endline, which is similar to a word search game but with figures.

We use the gross and fine motor skills test scores and worker's BMI as measures of physical function.[12] Productivity outcomes included the level of output and labor supply. Level of output is measured by the number of roses processed.[13] We use daily attendance records of each worker as a measure of labor supply.

Other outcomes we examine are measures of economic decision-making, using results from the double-oral auction game in which participants are assigned roles as buyers/sellers, and trade in a simulated market given a price/cost schedule (Appendix B). The outcome measures are total profit gained from the auction of three consecutive rounds, whether the participant transacted when she should have transacted at equilibrium given her price/cost schedule (i.e., efficient transaction), as well as whether transacted when she should not have (i.e., inefficient transaction).

All outcomes explained above were pre-specified as primary outcomes in the AEA RCT Registry, with the exception of the dictator, ultimatum, and trust game measures, which were pre-specified as secondary outcomes (Park and Kim, 2017).

3.3. Study sample and randomization balance

Our main study sample consists of workers employed at the floriculture farm for at least one month. Typically, they work eight-hour shifts, from 7 am to 4 pm with a one-hour lunch break, five days a week (Panel B of Fig. 2), earning 30 Ethiopian Birrs per day (equivalent to approximately 1.30 US dollars), paid every two weeks.[14] Table 2 presents summary statistics for the treatment (Column 2) and the control groups (Column 3), and the difference between control and treatment groups (Columns 4 and 5).

Panels A depicts respondent characteristics at baseline, and Panel B summarizes key outcome variables at baseline. On average, workers in our sample are 26 years old, 84% being female. 31% are married, and are from households averaging 2.7 individuals. Education levels are modest, with workers having about 4 years of schooling. The total monthly household income averages 1329 ETB (equivalent to about 48 USD). The diet diversity score averages 3.2 food groups per day, which is lower than the cutoff of five food groups for MDD, with an average daily caloric intake of 1946 calories.[15] The prevalence of anemia among floriculture workers (17%) exceeds that of women in neighboring communities (11%) (EWEDP Project, 2015), though lower than the global prevalence of anemia (24.3%) (Gardner et al., 2023). Column 4 confirms successful randomization. Out of 39 difference-in-means tests, three differences are statistically significant at the 5% level, indicating overall balanced baseline characteristics.

As shown in Panel C, the attrition rate is 1% for the follow-up survey, balanced across treatment and control. Attrition rates for daily behavioral and productivity data are 20.3% and 14.7%, respectively. We illustrate attrition by week of outcome measurement for the behavioral and productivity data, which shows that there is no particular week in which many people exit (Figure A6). We find statistically significant differential attrition rate of 4.2 percentage points by treatment status for productivity data. To address this, we control for continued employment at the farm in all regressions. Additionally, for productivity outcomes, we mitigate attrition concerns by calculating Lee bounds (2009).

4. Estimation strategy

In this section, we outline the estimation approach to estimating the treatment effect on various outcomes. Our basic treatment effects specification, using both baseline and endline data, employs analysis of covariance (ANCOVA) expressed by the following equation:

$$y_{ij1} = \beta_0 + \beta_1 Treatment_{ij} + X'_{ij0}\Gamma + \delta y_{ij0} + \theta_j + \varepsilon_{ij} \tag{1}$$

where y_{ij1} is the outcome of interest for individual i working in greenhouse or packhouse j at endline ($t = 1$). The binary variable $Treatment_i$ equals 1 if the participant was assigned to the treatment group and 0 otherwise. β_1 represents the effect of being assigned to the treatment arm. X_{ij0} is a vector of individual i's characteristics, including demographic variables (e.g., age, marital status, and household size) and socioeconomic status (e.g., level of education, household income, and asset index) at baseline ($t = 0$). Additionally, baseline levels of the outcome variables, y_{ij0}, are controlled for to improve statistical power (Mckenzie, 2012), along with whether the individual continued working at the farm during the study period. The regression includes greenhouse/packhouse fixed effects, θ_j, and ε_{ij} denotes the unobserved error term which is assumed to be serially uncorrelated. The outcome variable, y_{ijt}, encompasses the participant's nutritional, behavioral, and labor productivity outcomes. For daily/weekly data, we additionally control for time (day/week) fixed effects, with standard errors clustered at the level of randomization (individual).[16]

Furthermore, we examine the temporal dynamics of the treatment effect by estimating following pooled OLS regression equation:

$$y_{ijt} = \beta_0 + \sum_{k=1}^{12} \beta_1^k \left(Treatment_{ij} \times [t = k]\right) + X'_{ij0}\Gamma + \delta y_{ij0} + \theta_j + \alpha_t + \varepsilon_{ijt} \tag{3}$$

where y_{ijt} denotes the outcome measures for individual i for $t = 0, \ldots, 12$, where $t = 0$ is the measure at baseline, $t = 1$ the first week

[12] The motor test was conducted using the Bruininks-Oseretsky Test of Motor Proficiency, Second Edition (BOT-2) which measures motor skills in the following eight areas: fine motor precision, fine motor integration, manual dexterity, bilateral coordination, balance, running speed and agility, upper-limb coordination, and strength. We aggregate the scores from these eight areas into fine motor test scores and gross motor test scores as outcomes.

[13] The number of roses processed is a combination of number of roses harvested for greenhouse workers and the number of roses sorted and bunched for packhouse workers, standardized at the greenhouse and packhouse levels.

[14] Based on the exchange rate of 23 birr = 1 US dollar in 2017.

[15] Recommended caloric intake for individuals aged 25–26 with a BMI of 20 ranges from 2200–2400 kcal/day for moderately active women and 2800–3000 kcal/day for moderately active men (FAO/WHO/UNU, 2001; USDA and HHS, 2020).

[16] We estimate the following pooled ordinary least squared (OLS) regression for daily/weekly data:

$$y_{ijt} = \beta_0 + \beta_1 Treatment_{ij} + X'_{ij0}\Gamma + \delta y_{ij0} + \theta_j + \alpha_t + \varepsilon_{ijt}, \tag{2}$$

where α_t denotes time fixed effects.

Table 2
Baseline characteristics and balance check.

	(1) Obs.	(2) Treatment Mean	(3) Control Mean	(4) Mean differences C - T	(5) Standard error
Panel A. Respondent Characteristics					
Age	347	25.37	25.95	0.584	(0.951)
Female	347	0.809	0.862	0.053	(0.040)
Married	347	0.324	0.305	−0.019	(0.050)
Household size	347	2.717	2.621	−0.096	(0.178)
Years of schooling	347	4.410	3.891	−0.520	(0.453)
Total household income (Ethiopian Birr)	347	1324	1333	9.405	(91.96)
Asset index[a]	347	0.090	−0.089	−0.179	(0.183)
Whether have land	347	0.069	0.040	−0.029	(0.024)
Number of livestock	347	1.578	0.690	−0.888	(0.524)
Panel B. Outcome Variables					
Dietary diversity score (1–10)	347	3.216	3.191	−0.026	(0.076)
Caloric intake/day	341	1943	1946	−3.487	(60.83)
Stress Index[a]	694	0.375	0.389	0.014	(0.062)
Positive affect[a]	347	−0.651	−0.727	−0.076	(0.069)
Negative affect[a]	347	0.096	0.048	−0.047	(0.091)
Prosociality index[a]	2276	−0.254	−0.303	−0.049	(0.053)
Dictator game: amount shared (out of 100)	344	43.08	41.15	−1.930	(1.494)
Dictator game: whether fair offer	344	0.686	0.634	−0.052	(0.051)
Ultimatum game: amount shared (out of 100)	344	43.90	44.62	0.721	(1.443)
Ultimatum game: whether fair offer	344	0.651	0.669	0.017	(0.051)
Ultimatum game: whether rejected offer	344	0.099	0.093	−0.006	(0.032)
Trust game: amount shared (out of 100)	333	43.75	46.64	2.886	(1.509)
Trust game: proportion shared in response	324	0.486	0.431	−0.055**	(0.017)
Cooperation Index[a]	1167	−0.472	−0.428	0.043	(0.066)
Team sorting game: Number of errors	311	4.389	3.968	−0.421	(0.425)
Team sorting game: Time taken (second)	311	170.8	168.5	−2.264	(5.041)
Help given during work (minute, greenhouse)	252	0.369	0.307	−0.063	(0.110)
Inter-colleague cooperation assessment[a]	293	−0.245	−0.274	−0.029	(0.080)
Attention index[a]	1110	−0.597	−0.430	0.167	(0.091)
Sorting game: Number of errors	333	11.78	4.596	−7.188***	(1.700)
Sorting game: Time taken (second)	333	278.3	298.0	19.64	(11.16)
Search game: Number of errors	231	2.316	3.904	1.587	(0.989)
Search game: Time taken (second)	229	366.8	390.4	23.60	(24.87)
Physical Function index[a]	1041	0.014	−0.014	−0.028	(0.062)
Fine motor test[a]	347	0.095	−0.094	−0.189	(0.107)
Gross motor test[a]	347	−0.010	0.009	0.019	(0.108)
Body mass index	347	19.85	20.06	0.212	(0.264)
Productivity Index[a]	5400	0.094	0.096	0.002	(0.020)
Number of roses processed[a]	1944	−0.075	−0.123	−0.047	(0.025)
Attendance rate	3456	0.898	0.910	0.011	(0.010)
Panel C. Attrition					
Follow-up survey attrition	347	0.012	0.000	−0.012	(0.008)
Behavioral games attrition					
Stress	2996	0.148	0.127	−0.021	(0.013)
Prosociality	5435	0.209	0.189	−0.020	(0.011)
Cooperation	3034	0.256	0.232	−0.024	(0.016)
Attention	2681	0.255	0.224	−0.031	(0.016)
Productivity data attrition	26,235	0.170	0.128	−0.042***	(0.004)

Notes: This table reports mean of selected variables at baseline and attrition. Columns 1–3 show a summary of the treatment and the control groups. Column 4 and 5 report mean difference and standard error from test of mean differences between treatment (T) and control (C). *, **, and *** denote significance at 10%, 5%, and 1%, respectively.
[a] Standardized.

of the intervention, and $t = 11, 12$ at follow-up. $[t = k]$ is an indicator variable for the kth week of the intervention. This specification will allow for the inference of the treatment effect for each week following baseline.

To address multiple hypotheses testing, we adopt two approaches. First, we compute summary indices by grouping behavioral outcome measures into domains and compute an average standardized treatment effect (ASTE) for several outcome variables within each domain (Finkelstein et al., 2012; Kling et al., 2007). Taking measures of stress as an example, we group the positive affect score (redefined so that higher values imply greater stress), negative affect score, and absolute change rate of the positive and negative affect scores into one domain and compute the z-score for each outcome in this domain. Then, we stack the standardized outcomes for all outcomes within this domain and estimate a single pooled OLS regression equation, while clustering standard errors at the individual level to estimate the ASTE. Where data frequency differs by outcome within a domain, we run a weighted pooled OLS regression to account for differences in frequency. Second, we account for multiple hypotheses testing within each domain by reporting adjusted p-values which control the family-wise error rate (FWER) using a step-down resampling procedure (Westfall and Young, 1993).

5. Results

5.1. Nutrition support take-up and crowding out

We first examine whether the nutrition support program improves overall nutritional intake and assess the possibility of crowding out. Panels A and B of Fig. 3 show that caloric intake improves across the entire distribution for the treatment group compared to the control group. Corresponding regression results in Panel A of Table 3 confirm that the treatment group consumed more nutrition in both quantity

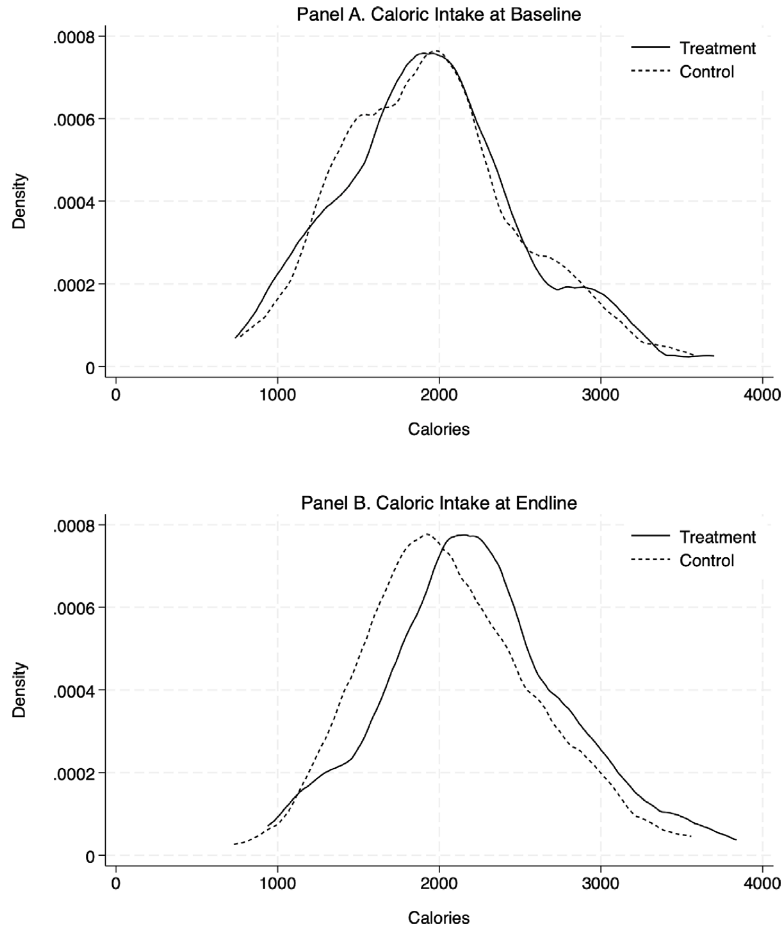

Fig. 3. Distribution of daily caloric intake at baseline and endline.
Notes: This figure shows kernel density graphs of caloric intake at the baseline survey conducted before the intervention (Panel A), and at the endline survey conducted on the last week of the intervention (Panel B).

and quality. On average, workers in the treatment group received breakfasts 33.8 times, corresponding to an 82.1% take-up rate (Column 1), and consumed an additional 223 calories per day compared to the control group (Column 2), indicating that the intervention equivalent to approximately 500 calories per day was not fully crowded out. This represents a substantial increase, given that many studies find evidence of complete crowding out either by reducing other meals for the same individual or redistributing nutrition within the household, leading to no net improvement in overall nutrition (Behrman and Hoddinott, 2005; Edmonds and Pavcnik, 2005; Jacoby, 2002). Dietary quality also improved, with dietary diversity increasing by 0.16 food groups (Column 3), and the proportion of workers meeting the minimum dietary diversity standard rising by 5.4 percentage points (Column 4). These improvements were driven by increased consumption of animal-source foods (Columns 5–8), which are nutrient-dense food groups often lacking in this population's diets.

We also find evidence of improvements in dietary quality at the household level, as shown in Panel B of Table 3. HDDS increased by 0.6 food groups in the treatment group, driven by increased intake of fruits, eggs, and dairy products (Columns 1–5). Column 6 indicates that there were some limited crowding out. The reduction in total household weekly food expenditure accounted for only 26% of the total weekly value of the breakfasts provided.[17]

[17] The decrease in household weekly food expenditure by 32 birr is 26% of the total weekly cost of the nutrition support per person, which was 125 birr.

5.2. *Effects on behavioral outcomes*

Having established that nutrition support improved workers' nutritional intake, we now examine its effects on behavioral outcomes. Most behavioral outcomes were collected in high frequency, enabling the analysis of weekly effects and their temporal dynamics (Figs. 4, A7, A8, A10, and A11). Each figure reports both the overall treatment effect pooling all weeks and the treatment effect for each specific week. Note that weeks 1 to 10 fall within the intervention period, while weeks 11 and 12 cover the period post-intervention.

Overall findings

We first show the impacts on four summary indices of behavioral outcomes in Table 4, which are the estimates of the ASTE in each behavioral domain as described in Section 4. Column 1 of Table 4 reports that the intervention reduced workers' stress levels by 0.23 SDs (95% CI: −0.275 to −0.181), suggesting a precisely estimated and economically meaningful reduction. Prosociality decreased by 0.06 SDs (95% CI: −0.115 to −0.009), indicating a modest but statistically significant effect. The impact on cooperation is smaller and imprecisely estimated, at −0.03 SDs (95% CI: −0.062 to 0.012). We find a decrease in attention by 0.08 SDs (95% CI: −0.175 to 0.013), but the wide confidence interval suggests uncertainty about the magnitude. Subsequent tables (Tables 5–8) detail the impacts on the components of each index, with summary index reproduced in the first column.

Table 3
Effects on intervention take-up and crowding-out.

Panel A. Worker-level nutrition outcomes

Variables	(1) Number of times eaten farm breakfast	(2) Caloric intake/day	(3) DDS (0–10)	(4) MDD	(5) Whether worker consumed	(6)	(7)	(8)
					Dairy	Meat & fish	Eggs	Vit-A-rich fruits & veg
Treatment	33.84***	222.9***	0.159*	0.054*	0.055**	0.066*	0.078***	−0.013
	(0.967)	(64.43)	(0.088)	(0.030)	(0.027)	(0.034)	(0.026)	(0.023)
Observations	347	336	341	341	347	347	347	347
R-squared	0.821	0.143	0.145	0.172	0.137	0.181	0.188	0.100
Control mean	0.000	2060	3.098	0.052	0.035	0.081	0.023	0.052

Panel B. Household-level nutrition outcomes

Variables	(9) HDDS (0–14)	(10) Whether household consumed	(11)	(12)	(13)	(14) Household food expenditure
		Dairy	Meat & fish	Eggs	Fruits	
Treatment	0.616***	0.098***	0.063	0.176***	0.210***	−31.98*
	(0.172)	(0.036)	(0.046)	(0.048)	(0.054)	(17.81)
Observations	345	345	345	345	345	345
R-squared	0.182	0.164	0.176	0.158	0.167	0.095
Control mean	6.793	0.075	0.195	0.144	0.259	210.99

Notes: This table reports treatment effects on worker-level (Panel A) and household-level (Panel B) nutritional outcomes to assess intervention take-up and crowding out. Column 1 shows results on the number of times the treatment group ate the nutrition support breakfast with control group fixed at zero. Column 2 presents results on daily caloric intake from 24-h recall. Columns 3 and 4 report dietary diversity score (DDS) and whether met the minimum dietary diversity score (MDD). Columns 5–8 report whether the worker consumed dairy products, meat and fish, eggs, or vitamin-A-rich fruits and vegetables in the past day. Columns 9–13 show results on the household dietary diversity score (HDDS) and whether the household consumed dairy products, meat and fish, eggs, or fruits in the past week. Column 14 reports effects on total household weekly food expenditures. All columns use ANCOVA using baseline and endline data with robust standard errors in parentheses (Eq. (1)). *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 4
Effects on summary indices.

Variable	(1) Stress index	(2) Prosociality index	(3) Cooperation index	(4) Attention index	(5) Physical function index	(6) Productivity index
Treatment	−0.228***	−0.062**	−0.025	−0.081*	−0.022	0.008
	(0.024)	(0.027)	(0.019)	(0.048)	(0.058)	(0.022)
Observations	8952	13,001	18,066	3836	1029	37,444
R-squared	0.025	0.041	0.111	0.130	0.208	0.064
Control mean	0.085	0.072	0.044	0.235	−0.012	0.024

Notes: This table reports summary indices of behavioral, physical, and productivity outcomes using average standardized treatment effect described in Section 4. Columns 1 to 4 present results on summary indices that aggregate outcomes reported in Tables 5 to 8 respectively. Columns 5 and 6 present results on summary indices that aggregate outcomes reported in Panel A and Panel B of Table 9, respectively. All columns use pooled OLS regression using outcomes measured from week 1 to week 12, controlling for week fixed effects with robust standard errors clustered at the individual level in parentheses (Eq. (2)). *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 5
Effects on behavioral outcomes: Stress.

Variable	(1) Stress index	(2) Emotional state	(3)	(4) Emotional stability	(5)
		Positive affect (standardized score)	Negative affect	Positive affect (absolute change rate)	Negative affect
Treatment	−0.228***	0.260***	−0.131***	−0.252***	−0.077**
	(0.024)	(0.039)	(0.045)	(0.024)	(0.030)
		{0.000}	{0.013}	{0.000}	{0.016}
Observations	8952	2238	2238	2238	2238
R-squared	0.025	0.114	0.066	0.073	0.025
Control mean	0.085	−0.020	0.062	0.589	0.713

Notes: This table reports effects on stress measured by emotional state and stability. Column 1 presents effects on the stress index which is an average standardized treatment effect of outcomes in Columns 2–5. Columns 2 and 3 report effects on standardized positive and negative affect levels as measures of emotional state from PANAS scores. Columns 4 and 5 report effects on absolute change rates of the PANAS scores as measures of emotional stability. All regressions include a standard set of controls. All columns use pooled OLS regression using outcomes measured from week 1 to week 12, controlling for week fixed effects with robust standard errors clustered at the individual level in parentheses (Eq. (2)). The Westfall–Young FWER-adjusted p-value in curly brackets. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Stress

First, we examine treatment effects on stress measured by emotional state and stability (Table 5). Columns 2 and 3 present the effects on positive and negative emotional states measured by PANAS, respectively. We find that nutrition support leads to improved emotional state or mood characterized by increased positive affect and decreased negative affect (Columns 2 and 3). Columns 4 and 5 show effects on emotional fluctuations or mood swings measured by changes in PANAS. Our findings indicate that nutritional support resulted in less fluctuations in both positive and negative affect, suggesting an improvement in

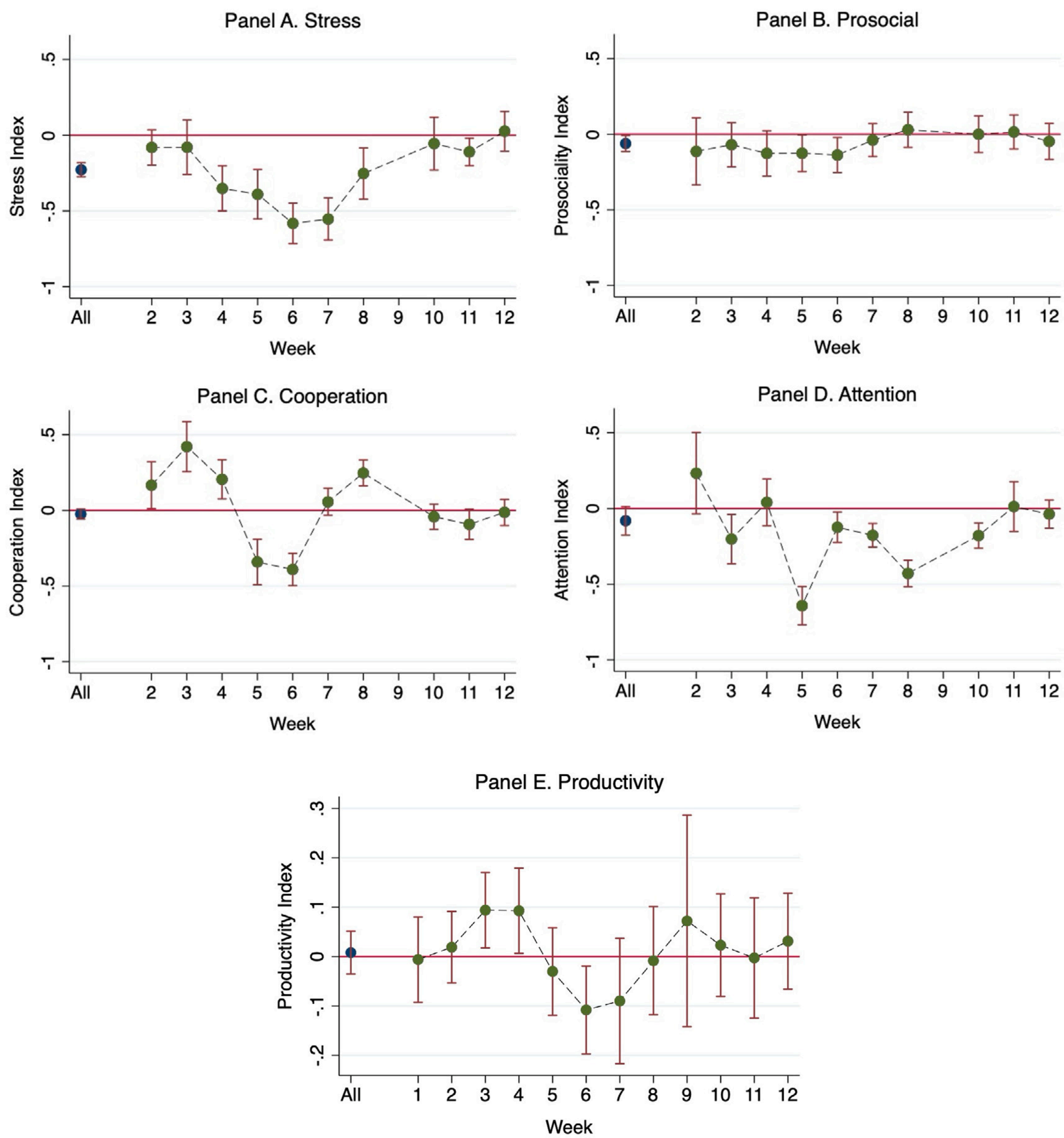

Fig. 4. Weekly treatment effects.
Notes: This figure presents weekly treatment effects on the stress index (Panel A), prosociality index (Panel B), cooperation index (Panel C), attention index (Panel D), and the productivity index (Panel E). In each panel, the first blue dot shows treatment effects on the index (average standardized treatment effects) over all weeks, estimated using Eq. (2). The subsequent green dots represent weekly effects on the index, estimated using Eq. (3). The red vertical lines indicate 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

emotional stability. These findings collectively suggest that nutrition support improved both emotional state and stability.

The effects on emotional states exhibit a distinct pattern over time (Panel A of Figs. 4 and A7). Positive(negative) affect gradually increases(decreases) until week 7, but this effect dissipates thereafter (Figs. 4 and A7). This pattern illustrates a case of hedonic adaptation which is a tendency of humans to quickly return to a relatively stable emotional state despite major positive or negative events (Frederick and Loewenstein, 1999). While empirical evidence on hedonic adaptation has centered around life events or circumstantial changes such as divorce, death of a spouse, unemployment, disability, and public policy, we demonstrate that hedonic adaptation tendencies also apply to nutrition support (Loewenstein and Ubel, 2008; Lucas, 2005; Lyubomirsky, 2011; Ubel et al., 2005).

Prosocial behaviors

We assess impacts on various aspects of prosocial behaviors, including generosity, fairness, trust, and reciprocity. Table 6 presents results on DG, UG, and TG. We find that workers in the treatment group exhibit more self-interest and less fairness compared to the control group, a pattern consistent across various measures—i.e., they allocate less to their partner and more likely to allocate less than half compared to the control group (Columns 2–5). While these estimates are statistically significant, the effect sizes are modest: the reductions in amount shared are −1.923, −0.968, and −1.315 birr for the dictator, ultimatum, and trust games, respectively, which corresponds to 2%–4% lower allocations relative to control means. These magnitudes are comparable to those found in other studies. For example, a large change in endowment rights, such as having an own earned property right, led to allocations about 20% lower than the control mean (Jakiela, 2015). In more

Table 6
Effects on behavioral outcomes: Prosocial Behaviors.

Variable	(1) Pro-sociality index	(2) Dictator game	(3)	(4) Ultimatum game	(5)	(6)	(7) Trust game	(8)
		Amount shared	Fair offer	Amount shared	Fair offer	Rejected offer	Amount shared	Amount shared in response (prop.)
Treatment	−0.062**	−1.923***	−0.047**	−0.968**	0.004	0.035***	−1.315**	0.027***
	(0.027)	(0.650)	(0.023)	(0.440)	(0.015)	(0.012)	(0.599)	(0.007)
		{0.034}	{0.135}	{0.135}	{0.782}	{0.031}	{0.135}	{0.001}
Observations	13,001	1900	1900	1899	1899	1899	1777	1727
R-squared	0.041	0.122	0.110	0.047	0.062	0.036	0.114	0.059
Control mean	0.072	46.474	0.811	49.037	0.879	0.045	47.794	0.461

Notes: This table reports effects on prosocial behaviors measured from the dictator game (DG), ultimatum game (UG), and trust game (TG). Column 1 presents effects on the prosociality index which is an average standardized treatment effect of outcomes in Columns 2–8. Columns 2–5 show effects on amount shared (a measure of generosity) and whether made a fair offer (a measure of fairness) from DG and UG. Column 6 reports effects on whether the receiver rejected offer in the UG. Columns 7 and 8 show effects on amount shared (a measure of trust) and the proportion of the amount shared in response by the receiver (a measure of reciprocity), respectively. All regressions include a standard set of controls. All columns use pooled OLS regression using outcomes measured from week 1 to week 12, controlling for week fixed effects with robust standard errors clustered at the individual level in parentheses (Eq. (2)). The Westfall–Young FWER-adjusted p-value in curly brackets. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

comparable interventions, such as early childhood education, the treatment group allocated 2%–3% less than the control group (Cappelen et al., 2020). While their estimates were not statistically significant, our high-frequency data allow us to detect significant effects of similar magnitude.

Also, the treatment group was more likely to reject an offer by 3.5 percentage points (Column 6). In the TG, as with DG and UG, workers in the treatment group allocated less to their partner, indicating lower levels of trust (Column 7). However, in the second step of TG, the treatment group reciprocated in greater amounts, reflecting a higher degree of reciprocity or trustworthiness (Column 8). Our findings align with experimental studies that find no or a negative relationship between nutrition and prosociality, contrary to the belief that hunger undermines prosociality (Häusser et al., 2019; Rantapuska et al., 2017).

There are several possible explanations for why nutrition support decreases prosocial behaviors. One explanation relies on the idea that prosocial behaviors are more likely to depend on incentive-related motives than altruism (Ligon and Schechter, 2012). In this view, prosociality is motivated by risk-sharing or reciprocity (Fafchamps, 1992; Townsend, 1994). Applying this to our setting, the workers in the treatment group may have become more self-sufficient with nutrition support, which would have in turn diminished the incentive to share as a mechanism of risk-sharing.

Another potential explanation is that nutrition support gives greater psychological bandwidth, helping workers to make a more welfare-enhancing choice. However, this argument is not fully supported as we do not find evidence on increased attention (Table 8).

A less likely explanation is based on the fact that all pairs of allocator and recipient in the prosocial games were formed within the same treatment or control group. Thus, allocators of prosocial games in the control group may have exhibited higher other-regarding preferences towards untreated control group recipients. In other words, out of empathy of not receiving the nutrition support, the control group may have acted more altruistically to other control group workers, as evidenced in studies on recipient deservingness that find recipient opportunity matters for allocator behavior (Engel, 2011; Cherry and Shogren, 2008). Although we are not able to test this using prosociality outcomes, as all games were played within the same group, we do not find evidence for greater other-regarding preferences in the control group using cooperation measures at work—the control group did not necessarily assess other control group workers more favorably nor help each other more than treatment group workers (Figure A9).

Panel B of Figs. 4 and A8 summarizes the weekly treatment effects on various measures of prosocial behaviors. In the DG, while there is high variance, we find that workers in the treatment group initially shared less than the control group, but this difference gradually disappears over time (Panel A of Figure A8). This pattern also applies to amount shared in the UG (Panel B of Figure A8). Further, the tendency of the treatment group to reject an offer gradually decreases as well (Panel B of Figure A8). The second figure of Panel C in Figure A8 shows that the treatment group reciprocates more, reflecting higher trustworthiness, but this effect also goes away after week four.

Cooperation

Table 7 shows measures of cooperation, including performance in team sorting games and help received or given during work among greenhouse workers. We do not find effects on cooperation measured by number of errors made and time taken in team sorting games (Columns 2 and 3). Similarly, the length of time spent providing help to other workers did not differ between the treatment and control groups (Columns 4). We also find no effects on inter-colleague cooperation assessment scores received. This result suggests that decreased prosociality is not necessarily linked to decreased cooperation, consistent with the findings of Dreber et al. (2014) that shows no relationship between altruism and cooperation in the context of repeated interactions.

Regarding the weekly treatment effects on team sorting tasks, the treatment group performs better in the first four weeks, completing the task in shorter time with fewer errors, but this effect not only disappears but even reverses in some later weeks (Panel C of Figs. 4 and A10). Consequently, pooling all of the weeks together, we find no effects on team sorting task performance.

Attention

We do not find evidence for a positive relationship between nutrition and attention using individual performance in sorting and search games. As shown in Table 8, we find that both the number of errors made and the time taken to complete the sorting task were higher for the treatment group (Columns 1 and 2). However, we find that the treatment had no effect on search game results.

Panel D of Figs. 4 and A11 shows weekly effects on workers' performance on individual sorting tasks. Similar to the team sorting tasks, we find that the treatment group performs better in terms of time taken in the first couple of weeks but become similar or even worse in some later weeks.

Overall, we find significant effects on psychosocial measures such as emotional well-being and prosociality, but do not find effects on behavioral outcomes involving real effort or decision-making.[18] Our findings are in line with other recent papers showing that income does not

[18] We also studied how nutrition support affects economic decision-making outcomes measured by double-oral auction games but did not find any effects (Table A1).

Table 7
Effects on behavioral outcomes: Cooperation.

Variable	(1) Cooperation index	(2) Team sorting game	(3)	(4) Cooperation during work	(5)
		Number of errors	Time taken (second)	Help given (min)	Inter-colleague cooperation assessment (standardized)
Treatment	−0.025	−0.067	−0.951	0.685	−0.056
	(0.019)	(0.089)	(1.542)	(1.167)	(0.042)
		{0.864}	{0.864}	{0.864}	{0.546}
Observations	18,066	1924	1924	13,675	543
R-squared	0.111	0.294	0.408	0.175	0.225
Control mean	0.044	1.766	115.85	15.481	−0.267

Notes: This table reports effects on cooperation measured by the number of errors and time taken in seconds in the team sorting task (Column 2 and 3), the length of time in minutes spent on helping other colleagues during work (Column 4), and inter-colleague cooperation assessment score received (Column 5). Column 1 presents effects on the cooperation index which is an average standardized treatment effect of outcomes in Columns 2–5. All regressions include a standard set of controls. All columns use pooled OLS regression using outcomes measured from week 1 to week 12, controlling for week fixed effects with robust standard errors clustered at the individual level in parentheses (Eq. (2)). The Westfall–Young FWER-adjusted p-value in curly brackets. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 8
Effects on behavioral outcomes: Attention.

Variable	(1) Attention index	(2) Individual sorting game	(3)	(4) Search game	(5)
		Number of errors	Time taken (second)	Number of errors	Time taken (second)
Treatment	−0.081*	0.934***	21.810***	0.022	−11.200
	(0.048)	(0.189)	(3.333)	(0.349)	(9.618)
		{0.000}	{0.000}	{0.998}	{0.894}
Observations	3836	1707	1707	212	210
R-squared	0.130	0.246	0.551	0.190	0.291
Control mean	0.235	1.599	165.53	2.860	273.46

Notes: This table reports effects on attention measured by individual sorting and search games. Column 1 presents effects on the attention index which is an average standardized treatment effect of outcomes in Columns 2–5. Columns 2–3 report effects on number of errors and time taken in seconds in the individual sorting game. Columns 4–5 show effects on number of errors and time taken in seconds in the search game. All regressions include a standard set of controls. Columns 1–3 use pooled OLS regression using outcomes measured from week 1 to week 12, controlling for week fixed effects with robust standard errors clustered at the individual level in parentheses (Eq. (2)). Columns 4–5 use ANCOVA using baseline and endline data with robust standard errors in parentheses (Eq. (1)). The Westfall–Young FWER-adjusted p-value in curly brackets. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

have significant effects on non-monetary real-effort decision-making or cognitive function (Carvalho et al., 2016; Fehr et al., 2022). Regarding the weekly effects, we find initial effects in the first several weeks that eventually fade away in the longer-term effects. This illustrates a consistent story that we find certain effects among treated workers in the first several weeks, but they eventually habituated and no longer show such effects in both psychosocial and behavioral aspects. This has important implications for evidence from short-term studies and especially lab experiments, which tend to measure short-term effects.

Potential experimenter demand effects

It is worth noting that the results on behavioral outcomes may be susceptible to experimenter demand effects, which refer to changes in behavior by subjects of the experiment due to cues from the experimenter about what constitutes appropriate behavior or Hawthorne effects (de Quidt et al., 2019). Although studies show that this is not a major concern in most canonical experimental tasks (de Quidt et al., 2018; Mummolo and Peterson, 2019), we conduct several exercises to show that this is unlikely to be a source of bias in this study.

First, when conducting the behavioral lab experiments, our protocol was designed such that all games or tasks are conducted within each treatment and control group, decreasing the salience of the treatment. Having the other players always be from the same treatment or control group obscures our interest in the nutrition treatment effect when participating in the games.

Second, the treatment effects on stress and prosociality have opposite directions—treatment group have better emotional well-being and are less prosocial. This is inconsistent with a simple story of experimenter demand effects driving our results, in which the treatment would both want to appear less stressed and more prosocial.

Third, time trends of the behavioral outcome measures in treatment and control provide suggestive evidence that the results are not likely to be driven by experimenter demand effects. Figure A12 shows coefficient estimates on stress and prosociality over time in both treatment and control relative to the omitted category which is the control group's baseline measurement. We find that for stress, control group mostly stays flat near zero, whereas the treatment group shows movement towards less stress. As for prosocial behaviors, both groups grow more prosocial over time, with the treatment group being slightly less prosocial. While it would raise concerns about experimenter demand effects had the treatment group stayed relatively flat when only the control responded more prosocially, we do not find that. An important caveat to these explanations, however, is that trends over time are not causal, and there may be various factors driving the trends.

Lastly, we use the information on individuals' degrees of agreeableness, which are similar to and has a strong positive correlation with what the social desirability scale measures (Edwards, 1957; Brajša-Žganec et al., 2011).[19] We do not find differential treatment effects by baseline agreeableness (Panels A-D, Table A2), nor a significant difference between treatment and control workers in the agreeableness scale at follow-up (Panel E, Table A2).

Taken together, these findings suggest that it is unlikely that experimenter demand effects might have changed respondents' likelihood to systematically misreport their affect or respond differently in behavioral games across the treatment and control groups. In addition, our

[19] Social desirability bias is typically measured using the Marlowe-Crowne Social Desirability Scale (Crowne and Marlowe, 1960). Previous studies relying on self-reports use this scale to assess experimenter demand effects by testing whether there is differential effects of social desirability bias between treatment and control (Dhar et al., 2022).

Table 9
Effects on physical function and labor productivity.

Panel A. Physical function Variable	(1) Physical function index	(2) Gross motor test scores	(3) Fine motor test scores	(4) BMI
		(standardized)		
Treatment	−0.022	0.045	−0.050	−0.142
	(0.058)	(0.104)	(0.096)	(0.202)
		{0.868}	{0.868}	{0.868}
Observations	1029	344	344	341
R-Squared	0.208	0.283	0.347	0.397
Control mean	−0.012	−0.020	−0.030	20.276

Panel B. Productivity Variable	(1) Productivity Index	(2) Number of roses processed (standardized)	(3) Attendance
Treatment	0.008	0.004	0.003
	(0.022)	(0.032)	(0.009)
		{0.934}	{0.934}
Observations	37,444	18,668	18,776
R-squared	0.064	0.153	0.043
Control mean	0.024	0.005	0.806

Notes: This table reports treatment effects on physical ability (Panel A) and productivity (Panel B). Panel A reports effects on gross and fine motor test scores (standardized), BMI, and self-report on whether nutrition support gave more strength. All regressions in Panel A use ANCOVA (Eq. (1)). Panel B outcomes include the number of roses harvested, sorted, or packed (standardized) as a measure of productivity and attendance rate as a measure of labor supply. Columns 1 and 2 of Panel B report coefficient on pooled OLS regression of daily productivity or attendance data from week 1 to week 12 with standard errors clustered at the individual level (Eq. (3)). All regressions include a standard set of controls. The Westfall–Young FWER-adjusted p-value in curly brackets. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

results are complemented by data obtained from the field such as the amount of time spent helping other colleagues, which we expect to be less susceptible to demand effects, and these results are not inconsistent with our lab results.

5.3. Effects on physical function and labor productivity

The summary indices on physical function (95% CI: −0.136 to 0.092 SDs) and labor productivity (95% CI: −0.035 to 0.051 SDs) show no effect of the nutrition support on these areas (Columns 5 and 6 of Table 4). The confidence intervals—particularly for labor productivity—are narrow and centered close to zero, allowing us to rule out even modest economically meaningful effects. Physical function index aggregates the gross and fine motor scores and BMI, and the productivity index the number of roses processed and attendance rate.

Physical function

Panel A of Table 9 shows that the nutrition support program had limited impacts on physical function measured by both fine or gross motor test scores (Columns 1 and 2). Although the treatment group reported feeling more strength and energy (Column 4), this was not reflected in the motor test scores or workers' BMI (Column 3).

Labor productivity

Figure A13 shows distribution of productivity, and Fig. 5 illustrates productivity over time in the treatment and control groups. These descriptive illustrations indicate that there is largely no difference in productivity levels between the treatment and control groups during and after the intervention in terms of both distribution and levels across time. Panel B of Table 9 shows that the nutrition support program did not improve labor productivity as measured by the number of roses processed (harvested, sorted, or packed). Furthermore, these estimates are precise, with the standard error at 0.032. Therefore, we can reject effect sizes larger than 0.067 (= 0.004 + (0.032 × 1.96)) SDs at the 5% significance level (Column 2).[20] Further, nutrition support did not lead to increases in labor supply measured by daily attendance (Column 3), which is also precisely measured. Aggregating both output levels and labor supply, we find a tight bound for the estimate, providing evidence for zero effect overall (Column 1). The null result contrasts with existing literature that shows a positive relationship between nutrition and productivity (Strauss, 1986; Croppenstedt and Muller, 2000; Chakrabarty and Grote, 2009; Wolgemuth et al., 1982), but supports literature that finds no relationship (Deolalikar, 1988; Immink and Viteri, 1981).

Panel E of Figs. 4 and A14 present the treatment effects on labor productivity by week. Productivity levels slightly increase in the first several weeks but stagnate until week 7 for the treatment group. Productivity levels seem to increase in weeks 9 and 10 but they are not statistically significant. Towards the end of the intervention and thereafter, we find no effect on productivity.

To address concerns about differential attrition in the productivity data, we first conduct Lee bounds analysis. Table A3 shows that our productivity estimates are unlikely to be affected by differential attrition, with the effect confidence intervals covering zero for all outcomes. We then present three complementary analyses to assess whether attrition could reflect unmeasured productivity gains. First, we compare baseline characteristics between attriting and non-attriting workers, defining attriters as those absent for four or more consecutive weeks without returning. We find no systematic differences other than age, suggesting that attrition is largely uncorrelated with observed baseline characteristics related to productivity (Table A4). Second, we restrict the analysis to the first half of the intervention (weeks 1–5), when attrition rates were more balanced across groups, and find no significant impact on productivity during this period (Table A5). Third, we were able to track attriting workers at endline through household visits and collected income data. Including the attriters in the analysis yields no significant treatment effects on income (Table A6). Together, these results suggest that differential attrition is unlikely to bias our productivity estimates or mask unmeasured productivity gains.

The null result on productivity is surprising as farm workers in our study are at the intersection of an occupation and calorie level where the marginal effect of additional calories on productivity could be large. Our main explanation for the null effect is that nutrition is not the main binding constraint for most workers in our study when it comes to improving productivity. When examining treatment effects on productivity by baseline caloric intake levels, we observe decreasing impact sizes as baseline caloric intake increases, though

[20] In absolute terms, the control group harvest mean is 861 roses per day per person and we are able to capture any changes greater than 45, which is 5% of the control group mean.

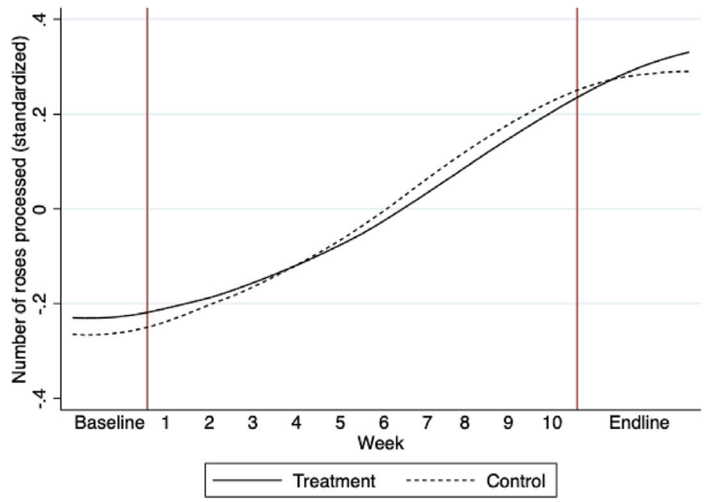

Fig. 5. Productivity over time.
Notes: This graph presents productivity over time over the study period using local polynomial smoothing. The two red vertical lines in Panel B indicate start and end of the intervention, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

not statistically significant (Figure A15). This suggests that nutrition may serve as a binding constraint for productivity improvements only among those with lower baseline intake levels. However, even for those with lower caloric intake, the overall relationship between nutrition and productivity appears weakly positive at best. This explanation aligns with recent studies on the economics of poverty that highlight the highly inelastic nature of productivity, as well as uncover other possible binding constraints to productivity such as financial concerns (Bessone et al., 2021; Kaur et al., 2021).[21]

Some explanations that we find unlikely include the presence of a ceiling for rose harvests due to, for example, limited market demand for roses. Relatedly, one may argue that workers were already at their maximum production capability at baseline with little room to improve. However, these reasons are not plausible as evidenced by continuously increasing levels of overall production in the farm over time (Fig. 5). The study was intentionally conducted during a period that included Valentine's Day when rose demand is highest throughout the year.

Another unlikely argument may be that the number of roses harvested over the study period is not a good measure of productivity because gains in harvests for cultivation workers are materialized much later in the future. However, our study period aptly covers the time required for a bud to open up, which is two to four weeks, and we do not find productivity improving in any of the later weeks of the intervention (Fig. 5). In addition, similar to the overall sample and greenhouse sub-sample, we do not find effects on productivity for the packhouse sub-sample for which the measure of productivity would not be lagged (Table A7).

One might also question the presence of negative spillovers from the control group to the treatment group out of grudge for not receiving the nutrition support, undermining treatment group's productivity. While spillovers are unlikely in the behavioral games as they were conducted in separate distant areas, field results, especially productivity, could be affected. However, in foresight of this, we designed the intervention such that negative spillovers are minimized: the control group was assured before the intervention that they would receive food vouchers after study completion, and measures were taken to mask the visibility of the treatment to the control group. Also, the nature of farm work and incentive structure minimize the potential for spillovers. For example, greenhouse workers, which comprises the majority of the sample, are assigned their own beds of roses to cultivate, and thus, are less likely to be influenced by poor performance or grudge from the control group. While packhouse workers work interdependently in pairs of sorters and bunchers, the paired incentive structure prevents intentional negative spillovers. Moreover, we do not observe significant differences between the greenhouse and packhouse workers in terms of effects on productivity (Table A7).

We acknowledge that our study focused on on-the-job productivity and did not capture potential reallocation of effort to other economic or non-economic activities. For example, improved nutrition may have increased workers' energy and psychosocial well-being, enabling them to invest more in part-time jobs or caregiving responsibilities. While we are unable to formally test these alternative channels, we provide suggestive evidence that workers in the treatment group did not shift their effort to other economic activities. Specifically, we find no significant effects on total income—which includes earnings from any wage employment, self-employed farming, and self-employed non-farming activities—and are able to reject income increases of 8% or more (Table A6). However, the treatment group may have increased nutritional investments in their households, as suggested by improvements in household diet diversity (Table 3).

5.4. Implications of behavioral outcomes for productivity

In this section, we discuss how our results on behavioral outcomes relate to results on productivity. We conduct subgroup analysis by levels of stress and prosocial behavioral outcomes at baseline—two behavioral domains for which the treatment effects were significant. We find that a good emotional state may partially contribute to productivity by increasing labor supply but not productivity. Column 1 of Table A8 shows that treatment effects on labor supply (attendance) is large and statistically significant for those with a better emotional state (Panel B), but not for workers who had a lower emotional state (Panel A). However, this effect did not translate into an overall increase in labor supply as shown in Column 3 of Panel B in Table 9, potentially due to hedonic adaptation. We do not find effects on productivity in either more prosocial or less prosocial groups (Table A9). This affirms the findings in the literature: while some studies find a positive association between social preferences and productivity (Carpenter and Seki, 2011), when addressing endogeneity using instrumental variables, the effect disappears (Barr and Serneels, 2009).

[21] Bessone et al. (2021) finds that significantly increasing nighttime sleep did not have any detectable effect on productivity, suggesting that productivity has low elasticity.

6. Conclusion

In this paper, using a randomized control trial combined with lab-in-the-field experiments in a floriculture rose farm setting, we investigate the relationship between nutrition and behavioral outcomes such as stress, social preference, cooperation, and attention, as well as physical function and labor productivity.

Regarding behavioral outcomes, our findings show that nutrition significantly impacts psychosocial measures that does not involve real effort, while no impact is found on real-effort tasks such as attention and cooperation. The nutrition support program enhances individuals' mental stability and self-interest. Specifically, we find improved emotional states characterized by higher positive affect and lower negative affect among treated workers, supporting the notion that hunger leads to irritable mood and better nutrition promotes a positive mood. Additionally, we find improved emotional stability over time in the treatment group. Interestingly, better nutrition did not necessarily make workers more prosocial; instead, fostered increased self-interest, possibly because they became more self-sufficient. We do not find effects on cooperation or attention, both of which involved real-effort tasks.

We also find that nutrition support did not have effects on physical function or productivity. Our precise measure of no effect on productivity challenges the link between nutrition and productivity in the context of high-effort work such as processing flowers, at least in the short term. This paper provides evidence against previous less rigorous empirical studies that found a positive relationship between nutrition and productivity decades ago, questioning the causal link between nutrition and productivity in modern work settings, particularly given the rapidly evolving nutritional state over recent decades (Black et al., 2013).

Another contribution of this paper lies in examining dynamic treatment effects, looking at how behaviors change over time. Weekly results on positive and negative affect, social preference, and attention collectively suggest a pattern wherein certain effects are prominent in the initial weeks but dissipate over time. This provides evidence for hedonic adaptation, a phenomenon for which there is limited evidence, especially concerning nutrition or social welfare programs. This partially explains why the effects of nutrition on behavioral outcomes are often mixed in the literature, as the outcomes are measured at different time points relative to the intervention.

Our results confer important implications for policy and interpreting other research. First, nutrition programs such as food transfers and school or work meal programs may indeed influence behavioral outcomes, albeit with varying effects. Also, while nutrition support programs could be beneficial for important outcomes such as health and education, they may not be the most effective approach to improving productivity, particularly in tasks with lower physical demands. Lastly, the evidence of hedonic adaptation over time underscores the importance of considering the time frame of studies when interpreting the effects of nutrition on behavioral outcomes, highlighting an important caveat in the interpretation of lab and field experiments that measure short-term effects of nutrition.

CRediT authorship contribution statement

Seollee Park: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hyuncheol Bryant Kim:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2025.103613.

Data availability

Upon acceptance, we will deposit our dataset in the Harvard Dataverse repository and make it publicly accessible.

References

Barr, A., Serneels, P., 2009. Reciprocity in the workplace. Exp. Econ. 12, 99–112.
Bates, M., Lemay, E., 2004. The d2 test of attention: Construct validity and extensions in scoring techniques. J. Int. Neuropsychol. Soc. 10 (3), 392–400.
Batson, C., Powell, A., 2003. Altruism and prosocial behavior. In: Million, T., Lerner, M. (Eds.), Handbook of Psychology: Personality and Social Psychology. John Wiley & Sons, Inc., pp. 463–484.
Behrman, J.R., Hoddinott, J., 2005. Program evaluation with unobserved heterogeneity and selective implementation: The Mexican PROGRESA impact on child nutrition. Oxf. Bull. Econ. Stat. 67 (4), 547–569.
Benton, D., Donohoe, R., 1999. The effects of nutrients on mood. Public Heal. Nutr. 2 (3a), 403–409.
Berg, J., Dickhaut, J., McCabe, K., 1995. Trust, reciprocity, and social history. Games Econom. Behav. 10, 122–142.
Bessone, P., Rao, G., Schilbach, F., Schofield, H., Toma, M., 2021. The economic consequences of increasing sleep among the urban poor. Q. J. Econ. 136 (3), 1887–1941.
Black, R., Victora, C., Walker, S., Bhutta, Z., Christian, P., de Onis, M., Ezzati, M., Grantham-Mcgregor, S., Katz, J., Martorell, R., Uauy, R., 2013. Maternal and child undernutrition and overweight in low-income and middle-income countries. Lancet 382 (9890), 427–451.
Bliss, C., Stern, N., 1982. Palanpur: the economy of an Indian village.
Brajša-Žganec, A., Ivanović, D., Kaliterna, L., 2011. Personality traits and social desirability as predictors of subjective well-being. Psihol. Teme 20 (2), 261–276.
Camerer, C., Hogarth, R., 1999. The effects of financial incentives in experiments: A review and capital-labor-production framework. J. Risk Uncertain. 19 (1-3), 7–42.
Campante, F., Yanagizawa-Drott, D., 2015. Does religion affect economic growth and happiness? Evidence from Ramadan. Q. J. Econ. 130 (2), 615–658.
Cappelen, A., List, J., Samek, A., Tungodden, B., 2020. The effect of early childhood education on social preferences. J. Political Econ. 128 (7), 2739–2758.
Carpenter, J., Seki, E., 2011. Do social preferences increase productivity? Field experimental evidence from fishermen in Toyama Bay. Econ. Inq. 49 (2), 612–630.
Carvalho, L., Meier, S., Wang, S., 2016. Poverty and economic decision-making: Evidence from changes in financial resources at payday. Am. Econ. Rev. 106 (2), 260–284.
Chakrabarty, S., Grote, U., 2009. Child labor in carpet weaving: Impact of social labeling in India and Nepal. World Dev. 37 (10), 1683–1693.
Cherry, T., Shogren, J., 2008. Self-interest, sympathy and the origin of endowments. Econom. Lett. 101 (1), 69–72.
Croppenstedt, A., Muller, C., 2000. The impact of farmers' health and nutrition status on their productivity and efficiency: Evidence from Ethiopia. Econ. Dev. Cult. Chang. 48, 475–502.
Crowne, D., Marlowe, D., 1960. A new scale of social desirability independent of psychopathology. J. Consult. Psychol. 24 (4), 349.
Danziger, S., Levav, J., Avnaim-Pesso, L., 2011. Extraneous factors in judicial decisions. PNAS 108, 6889–6892.
Dasgupta, P., 1993. An inquiry into well-being and destitution.
Dasgupta, P., Ray, D., 1986. Inequality as a determinant of malnutrition and unemployment. Theory Econ. J. 96, 1011–1034.
Dasgupta, P., Ray, D., 1987. Inequality as a determinant of malnutrition and unemployment. Policy Econ. J. 97, 177–188.
de Quidt, J., Haushofer, J., Roth, C., 2018. Measuring and bounding experimenter demand. Am. Econ. Rev. 108 (11), 3266–3302.
de Quidt, J., Vesterlund, L., Wilson, A., 2019. Experimenter demand effects. In: Schram, A., Ule, A. (Eds.), Handbook of Research Methods and Applications in Experimental Economics. Edward Elgar, pp. 384–400.
Dean, E., Schilbach, F., Schofield, H., 2018. Poverty and cognitive function. In: Barrett, C., Carter, M., Chavas, J. (Eds.), The Economics of Poverty Traps. University of Chicago Press.

Deolalikar, A., 1988. Nutrition and labor productivity in agriculture: Estimates for rural South India. Rev. Econ. Stat. 70, 406–413.

Dhar, D., Jain, T., Jayachandran, S., 2022. Reshaping adolescents' gender attitudes: Evidence from a school-based experiment in india. Am. Econ. Rev. 112 (3), 899–927.

Dreber, A., Fudenberg, D., Rand, D., 2014. Who cooperates in repeated games: The role of altruism, inequity aversion, and demographics. J. Econ. Behav. Organ. 98, 41–55.

Edmonds, E., Pavcnik, N., 2005. Child labor and schooling responses to anticipated income in South Africa. J. Dev. Econ. 81 (2), 386–414.

Edwards, A., 1957. The Social Desirability Variable in Personality Assessment and Research. The Dryden Press.

Engel, 2011. Dictator games: a meta study. Exp. Econ. 14, 583–610.

Fafchamps, M., 1992. Solidarity networks in preindustrial societies: Rational peasants with a moral economy. Econ. Dev. Cult. Chang. 41 (1), 147–174.

FAO, FHI 360, 2016. Minimum Dietary Diversity for Women: A Guide for Measurement. FAO.

FAO/WHO/UNU, 2001. Human Energy Requirements. Report of a Joint FAO/WHO/UNU Expert Consultation. tech. rep. No. 1, Food Agriculture Organization of the United Nations, Rome.

Fehr, D., Fink, G., Jack, B.K., 2022. Poor and rational: Decision-making under scarcity. J. Political Econ. 130, 2862–2897.

Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J., Allen, H., Baicker, K., The Oregon Health Study Group, 2012. The Oregon health insurance experiment: Evidence from the first year. Q. J. Econ. 127, 1057–1106.

Forsythe, R., Horowitz, J., Savin, N., Sefton, M., 1994. Fairness in simple bargaining experiments. Games Econom. Behav. 6, 347–369.

Frederick, S., Loewenstein, G., 1999. Hedonic adaptation. In: Kahneman, D., Diener, E., Schwarz, N. (Eds.), Well-Being. The Foundations of Hedonic Psychology. Russell Sage, pp. 302–329.

Gardner, W.M., Razo, C., McHugh, T.A., Hagins, H., Vilchis-Tella, V.M., Hennessy, C., Taylor, H.J., Perumal, N., Fuller, K., Cercy, K.M., Zoeckler, L.Z., Chen, C.S., Lim, S.S., Aali, A., Abate, K.H., Abd-Elsalam, S., Abdurehman, A.M., Abebe, G., Abidi, H., Aboagye, R.G., Abolhassani, H., Aboye, G.B.A., Abtew, Y.D., Accrombessi, M.M.K., Adane, D.E.A., Adane, T.D., Addo, I.Y., Adesina, M.A., 2023. Prevalence, years lived with disability, and trends in anaemia burden by severity and cause, 1990–2021: findings from the Global Burden of Disease Study 2021. Lancet Haematol. 10 (9), e713–e734.

Gilliot, M., Baumeister, R., Dewall, N., Maner, J., Plant, E., Tice, D., Brewer, L., Schmeichel, B., 2007. Self-control relies on glucose as a limited energy source: Willpower is more than a metaphor. J. Pers. Soc. Psychol. 92 (2), 325–336.

Gómez, G., Monge-Rojas, R., Vargas-Quesada, R., Previdelli, A., Quesada, D., Kovalskys, I., Herrera-Cuenca, M., Cortes, L., García, M., Liria-Domínguez, R., Rigotti, A., Fisberg, R., Ferrari, G., Fisberg, M., Brenes, J., 2024. Exploring the FAO minimum dietary diversity indicator as a suitable proxy of micronutrient adequacy in men and women across reproductive and non-reproductive ages in 8 Latin American countries. Food Nutr. Bull. 45 (2_suppl), S55–S65.

Grant, D., Berg, E., 1948. A behavioral analysis of degree of reinforcement and ease of shifting to new responses in Weigl-type card-sorting problem. J. Exp. Psychol. 38, 404–411.

Güth, W., Schmittberger, R., Schwarze, B., 1982. An experimental analysis of ultimatum bargaining. J. Econ. Behav. Organ. 3 (4), 367–388.

Haushofer, J., Fehr, E., 2014. On the psychology of poverty. Science 344 (6186), 862–867.

Häusser, J.A., Stahlecker, C., Mojzisch, A., Leder, J., Lange, P.A.V., Faber, N.S., 2019. Acute hunger does not always undermine prosociality. Nat. Commun. 10 (1), 1–10.

Headey, D., Hoddinott, J., Park, S., 2017. Accounting for nutritional changes in six success stories: A regression-decomposition approach. Glob. Food Secur. 13, 12–20, [Stories of Change in Nutrition].

Hoddinott, J., Maluccio, J.A., Behrman, J.R., Flores, R., Martorell, R., 2008. The impact of improving nutrition during early childhood on education among Guatemalan adults. Lancet 371 (9610), 411–416.

Immink, M., Viteri, F., 1981. Energy intake and productivity of Guatemalan sugarcane cutters: An empirical test of the efficiency wage hypothesis, part I. J. Dev. Econ. 9, 251–271.

Jacoby, H.G., 2002. Is there an intrahousehold flypaper effect? Evidence from a school feeding program. Econ. J. 112 (476), 196–221.

Jakiela, P., 2015. How fair shares compare: Experimental evidence from two cultures. J. Econ. Behav. Organ. 118, 40–54.

Kaur, S., Mullainathan, S., Oh, S., Schilbach, F., 2021. Do financial concerns make workers less productive?. NBER Work. Pap. 28338.

Kling, J., Liebman, J., Katz, L., 2007. Experimental analysis of neighborhood effects. Econometrica 75, 83–119.

Kraut, H., Muller, E., 1946. Calorie intake and industrial output. Science 104, 495–497.

Lee, D., 2009. Training, wages, and sample selection: Estimating sharp bounds on treatment effects. Rev. Econ. Stud. 76 (3), 1071–1102.

Ligon, E., Schechter, L., 2012. Motives for sharing in social networks. J. Dev. Econ. 99 (1), 13–26.

Loewenstein, G., Ubel, P., 2008. Hedonic adaptation and the role of decision and experience utility in public policy. J. Public Econ. 92 (8-9), 1795–1810.

Lucas, R., 2005. Time does not heal all wounds: A longitudinal study of reaction and adaptation to divorce. Psychol. Sci. 16 (12), 945–950.

Lyubomirsky, S., 2011. Hedonic adaptation to positive and negative experiences. In: Folkman, S. (Ed.), Oxford Handbook of Stress, Health, and Coping. Oxford University Press, pp. 200–224.

Marla, K., Padmaja, R., 2023. Analyzing gender differentials in dietary diversity across urban and peri-urban areas of Hyderabad, India. BMC Nutr. 9 (1), 36.

Mazumdar, D., 1959. The marginal productivity theory of wages and unemployment. Rev. Econ. Stud. 26 (3), 190–197.

Mckenzie, D., 2012. Beyond baseline and follow-up: The case for more T in experiments. J. Dev. Econ. 99 (2), 210–221.

Mentzakis, E., Mestelman, S., 2013. Hypothetical bias in value orientations ring games. Econ. Lett. 120 (3), 562–565.

Mummolo, J., Peterson, E., 2019. Demand effects in survey experiments: An empirical assessment. Am. Political Sci. Rev. 113 (2), 517–529.

Park, S., Kim, H., 2017. The short and long-term effects of hunger on behavioral outcomes, labor productivity, and economic decision-making. AEA RCT Regist..

Rantapuska, E., Freese, R., Jääskeläinen, I.P., Hytönen, K., 2017. Does short-term hunger increase trust and trustworthiness in a high trust society? Front. Psychol. 8 (NOV), 289593.

Reynolds, L. (Ed.), 1976. Pure theory of underdeveloped economies. In: Agriculture in Development Theory. Yale University Press, pp. 84–108.

Ridley, M., Rao, G., Schilbach, F., Patel, V., 2020. Poverty, depression, and anxiety: Causal evidence and mechanisms. Science 370 (6522), eaay021.

Schilbach, F., Schofield, H., Mullainathan, S., 2016. The psychological lives of the poor. Am. Econ. Rev.: Pap. Proc. 106 (5), 435–440.

Schofield, H., 2018. The economic costs of low caloric intake: Evidence from India. Unpubl. Manuscr..

Schofield, H., 2020. Ramadan fasting and agricultural input. Unpubl. Manuscr..

Singh, S., Jones, A., DeFries, R., Jain, M., 2020. The association between crop and income diversity and farmer intra-household dietary diversity in India. Food Secur. 12 (2), 369–390.

Stiglitz, J., 1974. Alternative theories of wage determination and unemployment in LDC's: The efficiency wage model. Cowles Found. Discuss. Pap. 357.

Strauss, J., 1986. Does better nutrition raise farm productivity. J. Political Econ. 94 (2), 297–320.

Thomas, D., Frankenberg, E., Friedman, J., Habicht, J.-P., Hakimi, M., Ingwersen, N., Jones, N., McKelvey, C., Pelto, G., Sikoki, B., 2006. Causal effect of health on labor market outcomes: Experimental evidence. Calif. Cent. Popul. Res..

Townsend, R.M., 1994. Risk and insurance in village India. Econometrica 62 (3), 539.

Ubel, P., Loewenstein, G., Jepson, C., 2005. Disability and sunshine: can predictions be improved by drawing attention to focusing illusions or emotional adaptation. J. Exp. Psychol.: Appl. 11 (2), 111–123.

US Army Institute of Environmental Medicine, 1987. Nutritional status and physical and mental performance of special operations soldiers consuming the ration, lightweight, or the meal, ready-to-eat military field ration during a 30-day field training exercise.

USDA and HHS, 2020. Dietary Guidelines for Americans, 2020–2025, ninth ed..

Watson, D., Clark, L., Tellegen, A., 1988. Development and validation of brief measures of positive and negative affect: the PANAS scales. J. Pers. Soc. Psychol. 54 (6), 1063–1070.

Westfall, P., Young, S., 1993. Resampling-Based Multiple Testing: Examples and Methods for p-Value Adjustment. John Wiley & Sons.

Woldeyohannes, T., 2015. Female workers in flower farm industry: a study of socio-economic impacts of the job opportunity: case of Bishoftu city.

Wolgemuth, J., Latham, M., Hall, A., Chesher, A., Crompton, D., 1982. Worker productivity and the nutritional status of Kenyan road construction laborers. Am. J. Clin. Nutr. 36, 68–78.

World Bank, 2020. GDP per capita (current US$) - Ethiopia. World Bank: Data.

Yellen, J., 1957. The theory of unemployment in densely populated backward areas. Effic. Wages Model. Labor Mark. 22–40.