RESR Revista de Economia e Sociologia Rural
ISSN 1806-9479
ARTICLE

The impacts of undernutrition on labor productivity: empirical evidence for rural area in Brazil

Os impactos da subnutrição na produtividade do trabalho: evidência empírica para a área rural do Brasil

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How to cite: Marinho, E. L. L., França, J. M. S., Campêlo, G. L., & Badagnan, T. F. (2025). The impacts of undernutrition on labor productivity: Empirical evidence for rural area in Brazil. Revista de Economia e Sociologia Rural, 63, e293231. https://doi.org/10.1590/1806-9479.2025.293231

Abstract: This article investigates the impact of undernutrition on labor productivity in rural Brazil by analyzing the Nutritional Poverty Trap (NPT). It examines the effects of vitamin A, B1, B2, iron, and calorie intake on the income of household heads across the Agricultural, Non-agricultural, Self-employed, and other employment sectors. A variation of the Dubin and McFadden (1984) method is employed to correct for selection bias using multinomial logit models. The analysis is based on data from the Household Budget Surveys (POF) for the years 2002–2003, 2008–2009, and 2017–2018. The results suggest that, although rural workers' diets have improved over time, nutritional deficiencies persist in the Agricultural and Non-agricultural sectors, contributing to low labor productivity. These findings are explained by ongoing deficiencies in micronutrients and calorie intake, which serve as a central mechanism of the NPT by diminishing workers' physical and cognitive capacity, thereby limiting their income-generating opportunities and perpetuating the cycle of poverty.

Keywords: nutrition-based poverty trap, calorie intake, micronutrient deprivation, rural poverty.

Resumo: Neste artigo investigam-se os impactos da subnutrição sobre a produtividade do trabalho na área rural do Brasil analisando a Armadilha da Pobreza Nutricional (APN). Investiga-se o efeito da ingestão de vitaminas A, B1, B2, ferro e de calorias sobre as rendas dos chefes de famílias nos setores agrícola, não agrícola, conta-própria e outros empregos. Utiliza-se uma variação do método de Dubin e McFadden (1984) para a correção de viés de seleção baseado em modelos *Logit Multinomiais*. Os dados utilizados são das Pesquisas de Orçamento Familiar (POF) para os anos de 2002-2003, 2008-2009 e 2017-2018. Os resultados obtidos sugerem que, embora tenha havido melhora na alimentação dos trabalhadores rurais, ainda persistem problemas alimentares nos setores ocupacionais agrícola e não agrícola na zona rural, indicando baixa produtividade do trabalho. Esse resultado é explicado pela deficiência de micronutrientes e caloria que atuam como um mecanismo central da APN, ao reduzir a capacidade física e cognitiva dos trabalhadores, limitando suas oportunidades de geração de renda e perpetuando o ciclo da pobreza.

Palavras-chave: armadilha da pobreza nutricional, Ingestão de calorias, privação de micronutrientes, pobreza rural.

1. Introduction

The literature on economic development has increasingly emphasized the determinants of well-being as articulated in the United Nations' Sustainable Development Goals (SDGs), a global agenda set for 2030. Among the central components for achieving these goals is the reduction of malnutrition. In this context, the primary objective of this article is to examine the impacts of malnutrition on labor productivity in rural areas of Brazil.

The core research question is whether improvements in nutrient intake can significantly affect workers' earnings and, consequently, contribute to breaking the poverty trap in rural regions. From this perspective, public policy should prioritize the implementation of nutritional supplementation programs in conjunction with direct poverty alleviation strategies.

Seminal contributions linking wages, nutrition, and productivity—based on early formulations of efficiency wage theory—were developed by Leibenstein (1957), Mirrlees (1975), and Stiglitz (1976), among others. These studies posit that productivity is a non-linear function of nutritional intake, wherein increased caloric consumption leads to marginal productivity gains and, consequently, higher wages. Building on these theoretical insights, subsequent empirical literature has sought to validate the existence of nutritional poverty traps. For instance, Strauss (1986) quantified the effects of caloric intake on annual agricultural output and labor productivity in rural Sierra Leone between May 1974 and April 1975. His findings revealed significant and positive associations between caloric intake and household productivity.

More recent international studies have reinforced the linkages between rural poverty, undernutrition, and low labor productivity within socioeconomically vulnerable contexts. Research conducted by Zhou et al. (2023), Rathu Manannalage et al. (2023), and Golden et al. (2024) demonstrates—through diverse empirical methodologies and rural case studies—that nutritional deprivation extends beyond caloric insufficiency, encompassing specific micronutrient deficiencies that contribute directly to the formation of the Nutritional Poverty Trap (NPT).

Despite the growing global attention to the NPT, empirical research on this phenomenon remains limited within the Brazilian context. While recent studies have explored issues related to food security and rural poverty (Jesus et al., 2024; Marcelino & Cunha, 2024), there is a marked gap in the literature concerning the quantification of caloric and micronutrient deficiencies and their specific effects on the formation of the NPT, as well as on labor productivity and income.

This article seeks to address this gap by empirically investigating the existence of the NPT in rural Brazil. Its primary contribution lies in quantifying the effects of both caloric intake and specific micronutrients—such as iron and vitamins A, B1, and B2—on the income of rural household heads, thereby providing evidence of the direct impact of nutritional deficiencies on labor productivity.

Moreover, by focusing on the Brazilian rural context, this study contributes to bridging a geographic gap in the international literature, which has predominantly concentrated on Asian and African countries.

To achieve these objectives, the study applies a variation of the Dubin & McFadden (1984) methodology to correct for selection bias using multinomial logit models, following the approach proposed by Bourguignon et al. (2007). This method estimates individuals' probabilities of labor market participation and incorporates these probabilities as determinants of household heads' per capita income to assess the presence of the NPT in rural Brazil. The empirical analysis is based on data from the three most recent rounds of the Brazilian Household Budget Survey (Pesquisa de Orçamentos Familiares – POF), conducted by the Brazilian Institute of Geography and Statistics (IBGE) for the years 2002–2003, 2008–2009, and 2017–2018.

The findings provide critical evidence to support the design and improvement of intersectoral public policies, particularly in the fields of food security, health, and economic development. Identifying key nutrients associated with labor productivity can inform more targeted and effective food supplementation programs and conditional cash transfer policies, with the potential to break the cycle of the NPT.

Following this introduction, the paper is structured into five sections. Section 2 presents the theoretical foundation. Section 3 outlines the econometric model specifications and the methodological approach to addressing selection bias using multinomial logit models. Section 4 reports the estimation results. The final section offers concluding remarks.

2. Theoretical Foundation

The efficiency wage hypothesis postulates that in developing countries such as Brazil, which experience particularly low nutritional levels, workers are physically incapable of performing manual labor. Consequently, their productivity is low, leading to low wages, low purchasing power, and, in turn, low levels of nutrition—thus perpetuating the vicious cycle of poverty. This reduces the likelihood of workers escaping the nutritional poverty trap (Dasgupta & Ray, 1986; Leibenstein, 1957; Mazumdar, 1959; Mirrlees, 1975).

According to Mirrlees (1975), efficiency wage models based on nutrition suggest that higher wages could enhance workers' productivity as increased income enables them to purchase more food, becoming better nourished and therefore more willing and able to work. Similarly, Leibenstein (1957) argues that a worker's productivity is determined by their wage, as it enables the acquisition of food that provides energy, allowing the worker to be more productive. In line with this, Stiglitz (1976) notes that workers' productivity depends on the nutritional content of their diet, with more nutritious food consumption positively impacting productivity and, consequently, wages.

Thomas & Strauss (1997), in a study on the impact of health indicators on the wages of urban workers in Brazil between August 1974 and August 1975, found a significant positive impact on wages due to improved health and nutrition conditions among poor urban individuals. Conversely, for rural southern India, Deolalikar (1988) reported that caloric intake did not affect wages or productivity, suggesting that the human body might adapt to caloric deficits in the short term. However, the study found that weight-for-height influenced wages and productivity, indicating that malnutrition is a crucial determinant of productivity and wages.

In India, Swamy (1997) demonstrated that wages based on the nutrition-based efficiency wage model are rigid because reducing them lowers workers' productivity and increases the cost per efficiency unit. Barrett (2002) also examined how micronutrient deficiencies reduce physical and cognitive activity, thereby reducing labor productivity. Such deficiencies indirectly decrease productivity by increasing workers' susceptibility to illness and infections. Horton & Ross (2003), using World Bank data from 1994 to 1996, showed that iron deficiency in ten developing countries was associated with a variety of functional consequences with economic implications, such as mental deterioration in children and low labor productivity among adults. Similarly, Lorch (2001) highlighted that vitamin A deficiency is a severe form of malnutrition that weakens the immune system and causes blindness.

Micronutrient deficiencies can significantly impact workers' productivity and performance, as argued by Lukaski (2004). Vitamin B1 deficiency may cause weakness, reduced endurance, muscle loss, and weight loss; vitamin B2 deficiency can lead to skin changes, mucosal membrane alterations, and nervous system dysfunction; vitamin A deficiency may lead to appetite loss and increased infection susceptibility; and iron deficiency causes anemia, cognitive deterioration, and immune system anomalies.

In an analysis of micronutrient deficiencies in the United States, Lakdawalla et al. (2005) used linear probability models to examine how nutritional deficiencies varied with food prices, finding that lower prices improved nutrition, although obesity was an adverse effect of economic progress. A notable contribution to the specialized literature on nutrition, poverty, and wages is made by Weinberger (2003), who examined the impact of iron deficiency on labor productivity in rural India, though without analyzing the nutritional poverty trap.

Addressing this gap, Jha et al. (2009) tested the existence of a nutritional poverty trap for calories and four micronutrients (carotene, iron, riboflavin, and thiamine) in rural India from January to June 1994. Using Heckman's sample selection procedure proposed by Heckman (1979), they confirmed the existence of the nutritional poverty trap in ten cases. The authors concluded that micronutrient deficiencies significantly impacted agricultural productivity, especially for female workers.

In a study for Thailand, Tiwasing et al. (2019) examined the impact of micronutrient intake on the productivity of rice-producing families. Results showed that calcium, vitamin A, and iron intake had positive and significant effects on family income, while caloric intake had a negative effect. The labor market serves as a mechanism for income generation and opportunities to achieve good health and nutrition. According to Dasgupta & Ray (1986), labor market dynamics can be hampered by malnutrition, as it impairs the human body's capacity to perform income-generating tasks. Poverty can lead to malnutrition, which in turn causes low productivity and reduced wages, trapping a significant portion of the population in a nutritional poverty trap.

The capacity curve describes the relationship between the amount of work an individual can perform and the energy required for that work. In a stylized version of this relationship, as described by Jha et al. (2009), income is synonymous with nutrition, meaning that all income is converted into nutrition. For very low-income levels, most of the energy derived from food consumption goes to resting metabolism—the minimum calories required for basic bodily functions such as breathing and maintaining body temperature. According to FAO (Food and Agriculture Organization of the United Nations, 2001) data, this minimum energy requirement for a "reference man" in Brazil, weighing 65 kg, is 1900 kcal/person/day. During this phase, little energy is available for work, making the work capacity curve nearly flat. Once resting metabolism needs are met, additional energy is allocated to physical work.

As income increases, work capacity initially rises rapidly due to additional energy being directed toward physical labor. However, when the body's energy requirements are fully met, the capacity to perform work increases at a diminishing rate due to natural physiological limits. For very low-income levels, the situation exhibits increasing returns, while beyond a certain income level, diminishing returns to scale are observed.

Using data from rural China between 1929 and 1933, Zhou et al. (2023) analyzed the impact of climatic disasters on agricultural productivity, farmers' wages, and nutritional intake. In addition to caloric deficiency, they examined the effects of the Nutritional Poverty Trap (NPT) in relation to micronutrient deficiencies. With the exception of iron, they found evidence of causal endogeneity for other nutrients—including protein, calcium, and phosphorus—thus confirming the existence of the NPT.

Rathu Manannalage et al. (2023) constructed a cereal calorie deprivation index to measure household poverty in Sri Lanka, using data from the Household Income and Expenditure Surveys (HIES) for the period from 2006 to 2016. Their results indicated a slow decline in cereal calorie deprivation compared to income-based poverty estimates. Moreover, they observed significant disparities in calorie deprivation by gender, ethnicity, education level, occupation, income group of the household head, and household geographic location.

In rural regions of Madagascar between 2013 and 2020, Golden et al. (2024) identified a high prevalence of micronutrient deficiencies—particularly zinc, vitamin A, iron, and vitamin B12—with substantial variation across rural zones. These authors assessed the nutritional status of the population, finding that more than two-thirds of individuals were zinc-deficient, and approximately 24% exhibited signs of chronic inflammation.

3. Methodology

The database used in this study was derived from the Household Budget Surveys (POF) conducted by IBGE for the rural areas of Brazilian states during the periods 2002–2003, 2008–2009, and 2017–2018. Variables related to the category "reference person of the family," corresponding to the head of the household, were extracted. This individual was identified as the household member meeting at least one of the following conditions: (i) responsible for paying rent; (ii) responsible for monthly mortgage payments; or (iii) responsible for other housing-related expenses (condominium fees, taxes, utility services, etc.). In cases where no one met these criteria, the household designated someone they considered the family reference person. The age range for the head of the household was set at 18 years or older.

According to the POF, the term "family" is equivalent to a consumption unit, defined as a single resident or a group of residents sharing the same food source—using the same food stock and/or incurring common food-related expenses. In cases where no shared food stock or expenses existed, identification was based on housing expenses. The unit of analysis in this study corresponds to the reference person of the consumption unit, used as a proxy for the family reference person. All variables related to food consumption, calories, and micronutrients were derived from this database. At the geographic level, the POF stratification includes: the urban area of the state capital, the metropolitan region, and the rural area. Statistical stratification was conducted based on definitions implemented in the Master Sample, which uses information on total household income from the 2010 Census. The household could be located in either urban or rural areas.

The Agricultural Sector comprises individuals involved in agricultural and livestock activities, including producers, farmers, entrepreneurs in mixed crop and livestock production, leaseholders, seasonal laborers, farmhands, planters, farmers, and rural temporary workers. The Non-Agricultural Sector includes workers in industries such as construction, textiles, electronics, mechanics, steel, food and beverage, forestry, education, public administration, and service provision. This category includes workers residing in rural areas but not employed in the Agricultural sector.

The Self-Employment Sector consists of individuals operating their enterprises independently or with partners, without employing others, and possibly with help from unpaid household members. This category includes segments such as commerce, vehicle repair, retail fuel sales, construction and other services. The Other Jobs sector comprises categories such as employers (individuals operating their own businesses with at least one employee), unpaid helpers assisting household members, and those producing for self-consumption.

The choice of micronutrients was based on their relevance to Brazilians' diets, as identified by the Agência Nacional de Vigilância Nacional (ANVISA). The units for micronutrients (iron and vitamins A, B1, and B2) are expressed in milligrams, and energy is measured in kilocalories. Average food prices were selected based on their importance within the food category of the Brazilian household budget: cereals and beans are staple items; edible oil and sugar are intermediate goods; and milk is a relatively luxurious item for low-income individuals. Food prices were calculated based on real expenditure on these items divided by the quantity purchased for each household. Expenditure and income values were adjusted to January 2018

Brazilian reais using the IBGE National Consumer Price Index (INPC) and were weighted by the POF expansion factor to provide accurate population estimates.

Nutritional status and food prices were included in the earnings equation to capture the direct and indirect effects of food prices on agricultural income (Bardhan, 1984; Barrett & Dorosh, 1996; Behrman & Deolalikar, 1990; Datt & Olmsted, 2004; Gaiha, 1995; Lakdawalla et al., 2005; Pitt & Rosenzweig, 1986; Ravallion, 1990; Sah & Stiglitz, 1987).

Explanatory variables related to family characteristics include commonly used factors such as the head of household's age, average years of schooling, gender, and the number of male and female adults in the household. Average rainfall, measured in millimeters, has a direct relationship with rural sector activities, potentially influencing productivity and crop losses, thus affecting employment demand. Rainfall data were provided by the Instituto Nacional de Meteorologia (INMET). A control variable for whether the state is coastal reflects the effects of economic growth or stagnation, as states near the coast generally exhibit higher development levels. These variable influences job demand, as suggested in theoretical literature (Jha et al., 2009). Chart 1 presents the description of variables for the Multinomial Logit Model.

Chart 1 - Description of Variables for the Multinomial Logit Model

Dependent Variable	Description	Situation
Occup	Occupacional decision	0: Work in the Agricultural sector
		1: Work in the Non-agricultural sector
		2: Self-employement
		3 Other Jobs
Explanatory Variables for Family Characteristics:		
agehead	Years of age of the head of the family	Numeric
agehead^2	Squared value of the head of the family's age	Numeric
adultm	Number of adult males in the family	Numeric
sizehous	Number of components in the family	Numeric
adultf	Number of adult females in the family	Numeric
averainfall	Average rainfall	Numeric
dsex	Dummy variable indicating the sex of the head of the household	0 female
		1 male
dlocal	Dummy variable indicating the location	0 State is not located on the coast
		1 State is located on the coast

Source: Data compiled by the authors from the Brazilian household budget survey (POFs) conducted in 2002-2003, 2008-2009, and 2017-2018.

It is important to note that the POF allows for an indirect evaluation of food consumption trends through estimated expenditures on food purchased for household consumption and market prices. However, the survey has limitations: it does not provide information on individual consumption (except for the 2008–2009 POF), intrafamily food distribution, or the quantity of food consumed outside the household.

Thus, to calculate the contribution of each micronutrient to the total food consumption of each family and the total per capita calorie intake, the Nutritional Composition of Food Table provided by the IBGE was used. This table consolidates data regarding the nutritional composition of the foods in the POF. Studies on food consumption patterns in Brazil are still quite scarce. The POFs for 2002–2003, 2008–2009, and 2017–2018 are the only ones with nationwide geographic coverage, including both urban and rural areas of the country. However, this article focuses on the rural area, as the literature highlights that the population residing in rural areas is more vulnerable due to inadequate education, health, and basic sanitation services, among other issues. (Hoffmann & Kageyama, 2007).

Table 1 presents the statistics for these variables from the 2017-2018 POF survey. Except for the Other Jobs activity sector, which has the highest average monthly income, the other sectors show average monthly incomes close to and above R$ 4,000.00. Given the low standard deviations for the number of adult men and women in households across all activity sectors, it can be stated that this number does not exceed one individual per household. The highest average age of the head of household is observed in the Agricultural sector, while the lowest is in the Non-agricultural sector. In the other sectors, these averages are very close.

The number of family members is relatively low and homogeneous across all analyzed sectors, averaging three per household. Meanwhile, the average years of schooling of the head of household are highest in the Other Jobs sector and lowest in the Agricultural sector. The Non-agricultural and Self-employment sectors have similar values, but both are below the average of the Other Jobs sector. The prices of each food item (cereals, beans, oil, sugar, and milk) are very similar across all activity sectors and exhibit low dispersion. However, the price of beans is significantly higher than that of other food items in all sectors.

Table 1 - Descriptive Statistics of Variables

Variables	Agricultural	Non-Agricultural	Self-Employment	Other Jobs
	Mean	Mean	Mean	Mean
Total income of head of household	4411.540	4804.440	4197.73	9883.03
	(-269.17)	(71,095)	(104.86)	(411.43)
Number of adult males in the family	1.3	1.04	1.1	1.2
	(0.019)	(0.007)	(0.012)	(0.024)
Number of adult females in the family	1.1	1.2	1.1	1.2
	(0.017)	(0.007)	(0.012)	(0.024)
Age of household head (years)	51.3	42.7	47.5	46.4
	(0.362)	(0.129)	(0.221)	(0.469)
Number of family members	3.9	3.2	3.2	3.3
	(0.046)	(0.016)	(0.027)	(0.058)
Years of schooling of head of household	5.6	9.8	8.2	11.1
	(0.106)	(0.049)	(0.076)	(0.167)
Price of cereals	3.76	3.84	3.78	3.9
	(0.014)	(0.006)	(0.009)	(0.02)
Price of bean	11.11	11.23	11.08	11.38
	(0.033)	(0.015)	(0.023)	(0.053)
Price of oil	4.2	4.16	4.22	4.15
	(0.012)	(0.004)	(0.007)	(0.015)
Price of sugar	4.69	4.08	3.9	4.15
	(0.138)	(0.048)	(0.069)	(0.163)
Price of milk	2.43	2.53	2.55	2.52
	(0.011)	(0.004)	(0.007)	(0.014)

Source: Results obtained by the authors based on data from the 2017–2018 Household Budget Survey (POF) and INMET 2017–2018.

Note: The numbers in parentheses are the standard deviations.

Initially, a multinomial Logit model is employed using the variables listed in Chart 1. This model allows for estimating the marginal effects on the response probabilities: Prob(Ocup = 0), Prob(Ocup = 1), Prob(Ocup = 2), and Prob(Ocup = 3), where 0 represents working in the Agricultural sector, 1 represents working in the Non-agricultural sector, 2 represents Self-employment, and 3 represents Other Jobs sectors. The estimated signs of the parameters in Equation 1 will reveal how the explanatory variables influence individuals' occupational decisions in the labor market. In these terms, the multinomial Logit model to be estimated is as follows:

$$Prob\left(Ocup_i = j\right) = \frac{\exp\left(\beta_j^{'} x_i\right)}{1 + \sum_{l=1}^{3} \exp\left(\beta_l^{'} x_i\right)}, \quad j = 0,1,2,3. \tag{1}$$

where x_i is a *kx1* vector of observable explanatory variables for household heads. $\beta_j^{'}$ is a vector of parameters related to these variables to be estimated, with dimensions *1xk*.

These response probabilities will be used to construct factors that correct the selection bias problem in estimating the income Equation 5 presented in subsection 4.1. In this second stage, estimating the income equation alongside the Durbin-Wu-Hausman test will verify the hypothesis of NPT.

Among the sampling selection modalities, there is one that arises when the dependent variable is observed only for a defined subset of the population. For example, the variable income is only observed for individuals with a strictly positive workload. In simpler cases, where the observation of the variable of interest is determined by a binary variable, the problem of endogenous selection can be easily resolved through the procedure proposed by Heckman (1976), which consists of a two-stage regression over the system:

$$y_1 = x_1 \beta_1 + u_1 \tag{1a}$$

$$y_2 = 1\left[x_2 \delta_2 + v_2 > 0\right] \tag{1b}$$

where (1a) is the equation explaining the variable of interest as a function of a vector of observable characteristics x_1 and u_1 a disturbance term, called the structural equation; (1b) is the equation explaining the binary variable y_2 based on the vector of observable characteristics x_2 and unobservable characteristics v_2, called the selection equation; (x_1, x_2) are always observable, and the variable y_1 is observed only when $y_2 = 1$.

According to Heckman (1976), consistent estimators of β_1 and γ_1 can be obtained by Ordinary Least Squares (OLS) regression of y_{i1} on x_{i1} and $\hat{\lambda} \equiv \lambda\left(x_{i2}, \hat{\delta}_2\right)$, where δ_2 is an estimator of λ obtained from a prior probit estimation of (1b). Here, $\lambda(\cdot)$ represents the inverse Mills ratio, i.e., $\lambda\left(x_2, \delta_2\right) = \dfrac{\phi\left(x_2 \delta_2\right)}{\Phi\left(x_2 \delta_2\right)}$ [1]

In more complex models, where selection occurs through a multinomial discrete choice process, the problem is structured as follows, according to Bourguignon et al. (2007):

$$y_1 = x \beta_1 + u_1 \tag{2a}$$

[1] $\phi(\cdot)$ e $\Phi(\cdot)$ are, respectively, the density function and the cumulative distribution function of the Standard Normal.

$$y_j^* = z\gamma_j + \eta_j,\ j = 1,\ 2,...,\ M \tag{2b}$$

where the disturbances u_1 satisfy $E(u_1/x,z)=0$ and $V(u_1/x,z)=\sigma^2$. The variable j represents a categorical variable describing the agent's choice among M alternatives based on their "utilities" y_j^*; the vectors z and x contain variables explaining the alternatives and the variable of interest, respectively. Without loss of generality, it is assumed that the variable y_1 is observed if and only if category 1 is chosen, which occurs when: $y_1^* > \max_{j\neq 1}\left(y_j^*\right)$. This condition is equivalent to $\varepsilon_1 < 0$, where $\varepsilon_1 = \max_{j\neq 1}\left(y_j^* - y_1^*\right) = \max_{j\neq 1}\left(z\gamma_j + \eta_j - z\gamma_1 - \eta_1\right)$. As demonstrated by McFadden (1973), assuming the $\left(\eta_j\right)$' are independent and identically distributed with a Gumbel distribution, this specification leads to the multinomial logit model, where the response probability is: $P\left(\varepsilon_1 < 0/z\right) = \frac{\exp(z\gamma_1)}{\sum_j \exp\left(z\gamma_j\right)}$.

Starting from this expression, consistent estimates of the $\left(\gamma_j\right)$'s parameters can be easily obtained through maximum likelihood estimation. However, the problem remains of how to estimate the parameter vector β_1, considering that the disturbances u_1 may not be independent of all $\left(\eta_j\right)$', introducing correlation between explanatory variables and the disturbance term in equation (2a). Consequently, OLS estimates of β_1 are inconsistent.

By generalizing Heckman's (1976) procedure, Bourguignon et al. (2007) show that selection bias correction can be based on the conditional mean of u_1, such that: $E\left(u_1/\varepsilon_1<0,\Gamma\right) = \int \int_{-\infty}^{0} \frac{u_1 f\left(u_1,\varepsilon_1/\Gamma\right)}{P\left(\varepsilon_1<0/\Gamma\right)} d\varepsilon_1 du_1 = \lambda(\Gamma)$ where $\Gamma \equiv \{z\gamma_1, z\gamma_2,...,z\gamma_M\}$ and $f\left(u_1,\varepsilon_1/\Gamma\right)$ Γ={zγ1,zγ2,...,zγM}, and $f\left(u_1,\varepsilon_1/\Gamma\right)$) is the joint conditional density of u_1 and ε_1. They also conclude that, since the relationships between the M components of Γ and the corresponding M probabilities can be inverted, there exists a unique function μ that can replace λ such that $E\left(u_1/\varepsilon_1<0,\Gamma\right) = \mu\left(P_1,...,P_M\right)$.

Thus, consistent estimates of β_1 can be obtained through one of the following regressions: $y_1 = x_1\beta_1 + \mu\left(P_1,...,P_M\right) + w_1$ or $y_1 = x_1\beta_1 + \lambda(\Gamma) + w_1$ where w_1 is the residual independent on average of the regressors. However, to the extent that estimating a large number of parameters becomes necessary when there is a wide range of alternatives, constraints on $\mu\left(P_1,...,P_M\right)$ or, equivalently, on λ(Γ), must be imposed to keep the problem manageable. It is precisely around these constraints that proposed methods for bias correction in the literature differ.

In the method proposed by Dubin & McFadden (1984), the assumed hypothesis is linearity among disturbances, expressed in terms of the conditional mean of u_1 on the $\left(\eta_j\right)$'s by:

$$E\left(u_1/\eta_1,...,\eta_M\right) = \sigma \sum_{j=1,...M} r_j \left(\eta_j - E\left(\eta_j\right)\right),\ \text{com}\ \sum_{j=1...M} r_j = 0 \tag{3}$$

This implies that $E\left(u_1/\eta_1...\eta_M\right) = \sigma \sum_{j=2...M} r_j\left(\eta_j - \eta_1\right)$. From this condition and based on the multinomial logit model, Dubin & McFadden (1984) obtained: $E\left(\eta_j - \eta_1 \Big/ y_1^* > \max_{s\neq 1}\left(y_s^*\right),\Gamma\right) = \frac{P_j \ln\left(P_j\right)}{1-P_j} + \ln\left(P_1\right)$, $\forall j>1$, and proposed that the model described in (2a) and (2b) could be estimated using OLS via the following equation:

$$y_1 = x_1\beta_1 + \sigma \sum_{j=2...M} r_j \left(\frac{P_j \ln\left(P_j\right)}{1-P_j} + \ln\left(P_1\right)\right) + w_1 \tag{4}$$

When analyzing this procedure, Bourguignon et al. (2007) observed that hypothesis (3) imposed a specific form of linearity between u_1 and the Gumbel distributions of the (η_j)'s, thus restricting the class of allowed distributions for u_1. They then suggested a variation of the hypothesis that would make u_1 linear within a set of normal distributions, allowing, in particular, μ to also be normal with $E(u_1 / \eta_1 ... \eta_M) = \sigma \sum_{j=1...M} r_j^* \eta_j^*$, where r_j^* are the correlations between u_1 and the standardized normal variables $\eta_j^* = J(\eta_j) = \Phi^{-1}(G(\eta_j))$, j = 1,...M. Φ^{-1}represents the inverse cumulative distribution function of the normal distribution, and $G(\eta_j)$ is the cumulative distribution function of η_j. Moreover, given a sample selection, the authors derived the following conditional expectations: $E\left(\eta_1^* / y_1^* > \max_{s \neq}(y_s^*), \Gamma\right) = m(P_1)$ and $E\left(\eta_j^* / y_1^* > \max_{s \neq}(y_s^*), \Gamma\right) = m(P_j) P_j / (P_j - 1)$ where $m(P_j) = \int J(v - \log P_j) g(v) dv$, $\forall j$.

Thus, they concluded that, after modifying the hypothesis, the regression Equation 4 could be expressed as:

$$y_1 = x_1 \beta_1 + \sigma \left[r_1^* m(P_1) + \sum_{j=2...M} r_j^* m(P_j) \frac{P_j}{(P_j - 1)} \right] + w_1 \tag{5}$$

According to Equation 5, the factors or variables correcting selection bias are defined $m_0 = m(P_1)$ and $m_j = m(P_{j+1}) \frac{P_{j+1}}{(P_{j+1} - 1)}$ for *j=1,2,...,M-1*), where σr_1^*, σr_2^*, σr_3^*, ..., σr_M^* are the respective parameters to be estimated.

By applying Monte Carlo experiments to compare the performance of bias correction methods based on Multinomial Logit Models (MLM), the authors also found that, in most cases, the method proposed by Dubin and McFadden (1984) is preferable to the more commonly used methods such as Lee (1983) and the semi-parametric alternative proposed by Dahl (2002). The experiments also showed that the performance of the Dubin & McFadden (1984) model is highly sensitive to the imposed normalization constraint and that the suggested variation, although generally less robust than the original version, performs better when the normalization hypothesis is violated. Furthermore, it appears more capable of capturing strongly nonlinear selection terms.

Lastly, they concluded from the Monte Carlo simulations that selection bias correction based on the Multinomial Logit Model provides sufficiently good corrections in the selection equation, even when the independence of irrelevant alternatives (IIA) hypothesis is violated. According to the discussion in the introduction about Nutritional Poverty Trap (NPT), it can be inferred that the relationship between household head income and nutritional intake is nonlinear. For this reason, the nutrient variable and its square will be included as explanatory variables in the specification of Equation 5. Furthermore, in estimating equation 5, there is an issue of endogeneity between income and nutrient levels. Both variables are jointly determined in this model. After all, the worker's diet affects their income, and income, in turn, contributes to improving their diet. Therefore, in addition to correcting the selection bias issue in estimating Equation 5, it is also necessary to address the endogeneity problem.

Thus, the Durbin-Wu-Hausman test statistic, which assesses the endogeneity between these variables, can indicate the existence of NPT. An alternative way to verify the existence of NPT is to observe whether the estimated coefficients of the nutrient variable and its squared value are, respectively, negative and positive in the regression (5) (Jha et al., 2009). In this context, four income regressions are estimated using Equation 5, where the dependent variables are the per capita incomes of household heads in the Agricultural, Non-agricultural, Self-employment, and Other Jobs sectors. In addition to the factors that correct selection bias, the other explanatory variables used in the estimation of Equation 5 are described in Chart 2.

Chart 2 - Description of Variables for Regression Equation 5

Dependent Variables:
Natural logarithm of the total income of the head of household in the Agricultural sector. (lnrendt)
Natural logarithm of the total income of the head of household in the Non-agricultural sector. (lnrendt)
Natural logarithm of the total income of the head of household in the Self-employement sector. (lnrendt)
Natural logarithm of the total income of the head of household in the Other Jobs sector. (lnrendt)
Explanatory Variables:
- lnagehead: Natural logarithm of the years of age of the head of the household.
- lnagehead^2: Natural logarithm of the squared years of age of the head of the household.
- lnadultm: Natural logarithm of the number of adult males in the family.
- lnadultf: Natural logarithm of the number of adult females in the family.
- tamfam: Natural logarithm of the number of family components.
- anest: Years of average education of the head of the household.
- dsex: Dummy variable for the sex of the head of the household (0 for woman, 1 for man).
- lncalorie: Natural logarithm of the amount of calories per capita consumed by the head of the household.
- lncalorie^2: Natural logarithm of the squared amount of calories per capita consumed by the head of the household.
- lnvitB1: Natural logarithm of the amount of vitamin B1 per capita consumed by the head of the household.
- lnvitB1^2 : Natural logarithm of the squared amount of vitamin B1 per capita consumed by the head of the household.
- lnvitB2: Natural logarithm of the amount of vitamin B2 per capita consumed by the head of the household.
- lnvitB2^2: Natural logarithm of the squared amount of vitamin B2 per capita consumed by the head of the household.
- lnvitA: Natural logarithm of the amount of vitamin A per capita consumed by the head of the household.
- lnvitA^2: Natural logarithm of the squared amount of vitamin A per capita consumed by the head of the household.
- lniron: Natural logarithm of the amount of iron per capita consumed by the head of the household.
- lniron^2: Natural logarithm of the squared amount of iron per capita consumed by the head of the household.
- lnpcereals: Natural logarithm of the average price of cereals (rice, oats, maize, wheat, rye, and derivatives).
- lnpoil: Natural logarithm of the average price of edible oil.
- lnpsugar: Natural logarithm of the average price of sugar.
- lnpbeans: Natural logarithm of the average price of beans.
- lnpmilk: Natural logarithm of the average price of milk.
- averainfall: Average rainfall.
- dlocal: Dummy variable for location (0 if the state is not located on the coast, 1 if it is).

Source: Data compiled by the authors from the Brazilian household budget survey (POFs) conducted in 2002-2003, 2008-2009, and 2017-2018.

4. Results and Discussion

Table 2 presents the marginal effects estimated from the Multinomial Logit model (Equation 1). The data used are from the 2002–2003, 2008–2009, and 2017–2018 Household Budget Surveys (POF), according to the variables described at the end of Section 3.

The main findings from Table 2, focusing on variables with significant and consistent marginal effects across at least two POF periods, reveal the following: an increase in the household head's age reduces the probability of working in the Agricultural sector in the first two POF periods;

a higher number of male adults in the household increases the likelihood of working in the Agricultural sector during the last two POF periods.

Table 2 - Marginal Effects for the Sample of Household Heads in Rural Area of Brazil (2002-2003)

Variable	Agricultural		Non-agricultural		Self-employment		Other Jobs	
	dy/dx	P>|z|	dy/dx	P>|z|	dy/dx	P>|z|	dy/dx	P>|z|
agehead	-0.016	0.000	0.010	0.000	0.007	0.004	-0.002	0.218
$agehead^2$	0.000	0.000	0.000	0.000	0.000	0.849	0.000	0.000
Adultm	-0.014	0.101	0.012	0.099	0.002	0.844	0.000	0.986
Adultf	-0.036	0.000	0.045	0.000	-0.008	0.485	-0.002	0.724
Sizehous	-0.002	0.463	-0.020	0.000	0.016	0.000	0.006	0.000
Dsex*	-0.257	0.000	0.170	0.000	-0.022	0.374	0.108	0.000
Averainfall	0.000	0.425	0.000	0.000	0.000	0.000	0.000	0.756
Dlocal	-0.063	0.000	-0.007	0.444	0.033	0.006	0.037	0.000
Marginal Effects for the Sample of Household Heads in Rural Area of Brazil (2008 - 2009)								
Variable	**Agricultural**		**Non-agricultural**		**Self-employment**		**Other Jobs**	
	dy/dx	**P>|z|**	**dy/dx**	**P>|z|**	**dy/dx**	**P>|z|**	**dy/dx**	**P>|z|**
agehead	-0.014	0.001	0.007	0.146	0.006	0.176	0.002	0.273
$agehead^2$	0.0001	0.030	0.000	0.015	0.000	0.767	0.000	0.562
Adultm	0.077	0.000	0.019	0.266	-0.071	0.000	-0.025	0.002
Adultf	-0.032	0.105	0.125	0.000	-0.092	0.000	-0.001	0.918
Sizehous	0.001	0.903	-0.035	0.000	0.033	0.000	0.001	0.812
Dsex*	-0.055	0.103	0.113	0.000	-0.062	0.064	0.005	0.659
Averainfall	0.0000	0.018	0.000	0.010	0.000	0.479	0.000	0.591
Dlocal	-0.025	0.263	0.014	0.517	-0.007	0.776	0.017	0.061
Marginal Effects for the sample of Households Heads in Rural Area of Brazil (2017 -2018)								
Variable	**Agricultural**		**Non-agricultural**		**Self-employment**		**Other Jobs**	
	dy/dx	**P>|z|**	**dy/dx**	**P>|z|**	**dy/dx**	**P>|z|**	**dy/dx**	**P>|z|**
agehead	0.000	0.914	0.003	0.569	-0.003	0.322	0.001	0.454
$agehead^2$	0.000	0.015	0.000	0.003	0.000	0.146	0.000	0.711
Adultm	0.043	0.012	-0.040	0.034	-0.006	0.652	0.003	0.409
Adultf	0.054	0.005	-0.040	0.055	-0.014	0.364	0.000	0.919
Sizehous	-0.006	0.461	-0.005	0.515	0.007	0.223	0.004	0.015
Dsex*	-0.154	0.000	0.095	0.000	0.037	0.054	0.022	0.000
Averainfall	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.013
Dlocal	0.004	0.855	0.080	0.000	-0.087	0.000	0.003	0.567

Source: Results constructed by the authors.

Note: The significance level adopted was 5%. (*) The dummy variable and dy/dx represent a discrete change in the dummy variable from 0 to 1.

For the Non-agricultural sector: a 1% increase in the number of female adults in the household raises the probability of employment by 4.5 percentage points (p.p.) and 12.5 p.p. for the 2002–2003 and 2008–2009 POFs, respectively; larger household sizes reduce the probability of non-agricultural employment by 2.0 p.p. and 3.5 p.p. in the first two POFs, while Self-employment probabilities increase by 1.6 p.p. and 3.3 p.p., and the probabilities for Other Jobs increase by 0.63 p.p. and 0.40 p.p. in the first and last POFs, respectively.

For household heads' gender: male household heads, compared to females, have a 25.6 p.p. and 15.4 p.p. decrease in the probability of agricultural employment in the first and last POFs, respectively; conversely, their probability of non-agricultural employment increases by 17.0 p.p., 11.3 p.p., and 9.5 p.p. sequentially across the POFs and increases by 10.8 p.p. and 2.2 p.p. in the Other Jobs sector for the first and last POFs.

For the other findings: average rainfall reduces the likelihood of non-agricultural employment across all POFs and increases the likelihood of agricultural employment in the last two POFs; individuals residing in coastal states are more likely to be employed in Non-agricultural sectors and less likely in Self-employment for the last two POFs.

4.1. Results of NPT Estimation

Low-income workers with inadequate nutrition tend to exhibit low productivity, resulting in lower earnings. Similarly, undernourished individuals are less productive and earn less in the labor market. This bidirectional relationship introduces an endogeneity problem in Equation 5, creating a reverse causality issue. The NPT framework establishes this bidirectional relationship between earnings and nutritional intake. To detect this endogeneity problem, the Durbin-Wu-Hausman test can be used. Furthermore, this test can identify the presence of NPT related to a specific nutrient. The adopted significance level was 5%. This test was conducted for all micronutrients across all occupational sectors, with results presented in Table 3.

The synthesis of Table 3 presented in Table 4 below shows that the occupational sector Other Jobs did not present any cases of Nutritional Poverty Trap (NPT) for any of the micronutrients analyzed in the 2002-2003, 2008-2009, and 2017-2018 POF surveys.

Table 3 - Durbin-Wu-Hausman Test Results for NPT Existence

Sector/Nutrient	Hausman Test	Hausman Test	Hausman Test
	2003-2004 POF	2008-2009 POF	2017-2018 POF
Agricultural / Calories	30.21 (0.0000)	7.50 (0.0000)	6.91 (0.0310)
Non-Agricultural / Calories	1.99 (0.3704)	16.02 (0.0003)	14.42 (0.0007)
Self-employment /Calories	9.45 (0.0089)	1.62 (0.4460)	2.88 (0.2368)
Other Jobs /Calories	2.06 (0.3579)	0.52 (0.7706)	3.33 (0.1894)
Agricultural / Vit. B1	13.02 (0.0015)	1.90 (0.3871)	3.57 (0.1677)
Non-Agricultural / Vit. B1	30.21 (0.0000)	15.01 (0.0006)	10.68 (0.0048)
Self-employment / Vit. B1	3.44 (0.1792)	5.24 (0.0729)	1.05 (0.5930)
Other Jobs / Vit. B1	1.46 (0.4825)	1.12 (0.5715)	1.47 (0.4799)
Agricultural / Vit. B2	55.48 (0.0000)	1.68 (0.4319)	4.59 (0.1009)
Non-Agricultural / Vit. B2	34.48 (0.0000)	11.32 (0.0035)	14.99 (0.0006)
Self-employment / Vit. B2	4.66 (0.0971)	0.29 (0.8660)	5.22 (0.0736)
Other Jobs / Vit. B2	5.61 (0.0604)	0.77 (0.6811)	1.74 (0.4191)
Agricultural / Vit. A	20.16 (0.0000)	0.20 (0.9060)	6.12 (0.0469)
Non-Agricultural / Vit. A	2.14 (0.3436)	4.29 (0.1170)	4.05 (0.1320)
Other Jobs / Vit. A	1.16 (0.5606)	1.22 (0.5436)	1.01 (0.6044)
Agricultural / Iron	8.99 (0.0111)	3.30 (0.1924)	8.28 (0.0159)
Non-Agricultural / Iron	20.02 (0.0000)	9.97 (0.0069)	14.07 (0.0006)
Self-employment / Iron	3.88 (0.1436)	0.91 (0.6341)	1.95 (0.3775)
Other Jobs / Iron	3.90 (0.1436)	6.05 (0.9720)	1.24 (0.5373)

Source: Results constructed by the authors.
Note: p-Value in parentheses.

However, the Agricultural and Non-Agricultural sectors exhibited severe malnutrition issues. In the Agricultural sector, for the period 2002-2003, the hypothesis of endogeneity for all nutrients could not be rejected at a 5% significance level. In other words, these results demonstrate the presence of NPT for all nutrients.

Table 4 - NPT for Micronutrients and Calories for the Rural Area in Brazil

Sector	2002-2003 POF	2008-2009 POF	2017-2018 POF
Agricultural	Cal./Vit.B1, B2, A/Iron	Cal.	Cal./Vit.A/Iron
Non Agricultural	Vit.B1, B2/Iron	Cal./Vit.B1, B2/Iron	Cal./Vit.B1, B2/Iron
Other Jobs	-	-	-

Source: Results constructed by the authors.

4.2. Results of the Estimates of the Income Equations

The regression model in Equation 5 was estimated for all micronutrients across all occupational sectors for each period. However, to conserve space, only the results for the most recent period (2017-2018) are presented[2]. These results are detailed in Tables A1 to A5 in the Appendix.

Due to the possible endogeneity between total income and nutritional intake, the econometric strategy used to estimate Equation 5 was as follows: when endogeneity was not an issue, it was checked whether the residuals were homoscedastic. If so, Equation 5 was estimated using OLS. Otherwise, the equation was estimated using OLS with robust standard errors, adjusted for heteroscedasticity. The White/Koenker Test was used to identify heteroscedasticity in the OLS estimations. Since the power of traditional tests is sensitive to the normality assumption of residuals, this test relaxes that assumption.

In cases of endogeneity, if the residuals were homoscedastic, Equation 5 was estimated using Two-Stage Least Squares (2SLS). In this scenario, the estimated parameters of Equation 5 are more efficient compared to the Generalized Method of Moments (GMM). When model residuals were heteroscedastic, the equation was estimated using GMM, as it provides greater efficiency under heteroscedasticity. The Pagan-Hall Test was used to verify heteroscedasticity in the 2SLS model. According to Pagan & Hall (1983), traditional heteroscedasticity tests are valid only if heteroscedasticity is present solely in the estimated equation.

Following the empirical literature, five instruments were used for the nutritional intake variable in estimating Equation 5. These instruments were employed to address potential endogeneity in the estimation process: mother's education level: It is assumed that higher average maternal education can enable family members to consume nutrient-rich foods that promote a healthy lifestyle; age of the household head: This is a key determinant of calorie provision and consumption and may influence income generation; number of children under 10 years old: a larger number of children in this age group can complicate food distribution among adults and children; household size: larger households are more likely to have insufficient quantity and quality of food diversity; rainfall levels: rainfall affects agricultural production, impacting food prices and nutrition. (Babatunde et al., 2010; Behrman & Wolfe, 1984; Haddad & Bouis, 1991; Jha et al., 2009; Tiwasing et al., 2019).

The Sargan Test was used to assess the validity of instruments when Equation 5 was estimated using 2SLS, while the Hansen Test was used when estimated with GMM. Descriptions of these instrumental variables and the test results are presented in Tables A1 to A5 of the appendix. The test results confirmed the quality of the selected instruments. According to the results in Tables A1, A2, A3, A4, and A5 in the Appendix, the Agricultural sector exhibits NPT concerning

[2] The regression results for the years of the other POFs can be requested from each of the authors.

Calories and Iron. Meanwhile, the Non-agricultural sector shows NPT for Calories, Vitamin A, and Iron. The estimated positive coefficients and their negative squared terms for these variables in Equation 5 were statistically significant at the 5% level. This confirms a nonlinear relationship between total income and these nutrients, corroborating the NPT evidence identified by the Durbin-Wu-Hausman Test in Table 3.

For other occupational categories, the predicted coefficients and their squares for the nutrients were not statistically significant. With the exception of the Other Jobs sector, the years of schooling of the household head were positively correlated with total income in all regressions across all nutrients. This is a standard finding in most empirical studies linking education to labor market outcomes.

The estimated price coefficients for cereals showed the expected negative and significant signs for all micronutrients and vitamins in the Agricultural sector across all three POFs. In the Non-agricultural sector, this variable was statistically insignificant only for Vitamin A. For other sectors, it was not statistically significant. Conversely, the estimated coefficients for bean prices were positive and significant for micronutrients and calories in most occupational sectors, except the Other Jobs sector.

Regarding sugar prices, the estimated coefficients were positive and significant for Calories, Iron, and Vitamins A and B2 in the Agricultural sector. In the Non-agricultural sector, this result persisted only for Vitamins B1 and B2. In other sectors, the variable was not statistically significant. Meanwhile, milk prices were insignificant in all regressions. These positive and significant price coefficients contradict expectations, as lower prices generally suggest greater nutrient availability. Empirical studies typically associate higher food prices with negative and significant coefficients in income equations. (Bardhan, 1984; Gaiha, 1995; Jha et al., 2009; Ravallion, 1990).

Regarding household characteristics, a larger number of adult men in the household had a significant and positive effect on calorie consumption in all sectors except Other employment, Vitamin B1 in the Non-agricultural sector, Vitamin B2 in both Agricultural and Non-agricultural sectors, and Iron in the Agricultural, Non-agricultural, and Self-employment sectors. This finding suggests that more adults working in these sectors contribute to higher household income.

The number of adult women in the household had a positive and significant effect on Calories, Vitamin B1, and Iron in the Non-agricultural sector and Calories, Vitamins B1 and B2 in the Self-employment sector. For Vitamin A, neither the number of adult men nor adult women had a significant effect in any regression. These findings contrast with those of Jha et al. (2009). However, the age of the household head and its square were insignificant in most cases, consistent with Jha et al. (2009).

The estimated coefficient for the coastal variable (dlocal) was positive and significant in the regressions for Calories and Iron in the Agricultural sector and Vitamin A in the Non-agricultural sector. This evidence indicates that workers residing in coastal states tend to earn higher wages in these sectors compared to those in non-coastal states, possibly due to the greater economic dynamism of coastal regions (Jha et al., 2009).The average rainfall variable was not statistically significant in any regression for any sector. In other words, rainfall appears to have no influence on household head income across any activity sector.

5. Conclusions

The primary objective of this study was to assess the existence of the Nutritional Poverty Trap (NPT) by analyzing the effects of micronutrient intake—specifically Calories, Iron, and Vitamins A, B1, and B2—on total household income in rural Brazil.

The results indicate that the *Other Jobs* sector did not exhibit any evidence of NPT for any of the nutrients analyzed during the periods 2002–2003, 2008–2009, and 2017–2018. In the *Self-Employed* sector, a Non-Poverty Nutritional Area (NPNA) was observed for Caloric intake in 2002–2003, and evidence of an NPT was found for Vitamin A in 2008–2009. For the 2017–2018 period, no signs of an NPT were observed in this sector for any of the micronutrients studied. In contrast, the *Agricultural* sector presented strong evidence of NPT in 2017–2018, specifically for Calories, Iron, and Vitamin A. The *Non-Agricultural* sector, in the same period, exhibited NPT for all micronutrients except Vitamin A.

These findings are consistent with those of Jha et al. (2009), who demonstrated that NPT significantly affects labor productivity among agricultural workers, particularly women. Their study reported the presence of NPT in the agricultural sector for Calories, Iron, Vitamin A, and Vitamins B1 and B2.

Micronutrient deficiencies, as revealed in the periods under analysis, persist as a significant public health challenge in both the agricultural and non-agricultural sectors of rural Brazil. The results suggest that increasing household income among low-income populations and reducing the prices of nutrient-rich foods may enhance the dietary intake of essential nutrients in rural communities. This is consistent with existing economic literature, which underscores the importance of nutritional interventions in reducing extreme poverty and fostering economic development. Evidence from the fields of economics and public health consistently shows that better-nourished individuals are more productive workers.

An example of a relevant public policy initiative is Brazil's National Food and Nutrition Policy, established in 1999 by the Ministry of Health. This policy prioritizes the promotion of food and nutritional security for the entire population. The Ministry of Health has implemented various nutrition and public health programs targeting micronutrient deficiencies among at-risk groups—including infants, children, and pregnant women—through vitamin A supplementation, iron sulfate distribution, and mandatory food fortification (e.g., the enrichment of wheat and corn flour with iron and folic acid). Additionally, iodine is added to table salt in accordance with regulations issued by the National Health Surveillance Agency (Anvisa). These initiatives are further reinforced by programs such as the Brazil Without Hunger Plan and the National Micronutrient Supplementation Programs, including: *NutriSUS* (micronutrient powder fortification for children), the National Iron Supplementation Program (PNSF), and the National Vitamin A Supplementation Program (PNSVA).

Given these findings, the study emphasizes the need for long-term, multi-dimensional public nutrition policies. Such policies should include improved identification of target populations, regular monitoring of food consumption patterns, employment and income strategies focused on low-income groups, food price stabilization measures, support for the agri-food sector, and the promotion of nutritional education.

This study contributes to both the economic and nutritional literature by quantifying the impact of caloric and micronutrient deficiencies on the formation of the Nutritional Poverty Trap, and by demonstrating how these deficiencies undermine labor productivity. These results highlight the urgency of adopting integrated nutritional strategies to break the cycle of poverty in rural Brazil.

Authors contribution

ELLM: Conceptualization, formal analysis and methodology. JMSF: Project administration, supervision and writing – review & editing. GLC: Validation, visualization and writing – original draft. TFB: Data curation and investigation.

Financial support:

Nothing to declare.

Conflicts of interest

Nothing to declare.

Ethics statement

Not applicable.

Data Availability Statement

● Research data is available upon request.

- The microdata from Brazilian Household Budget Survey (POF/IBGE) (2002-2003) (2008-2009) (2017-2018)

https://www.ibge.gov.br/estatisticas/sociais/saude/24786-pesquisa-de-orcamentos-familiares-2.html?=&t=microdados

-INMET: Instituto Nacional de Meteorologia

https://bdmep.inmet.gov.br/Os dados da pesquisa estão disponíveis através do DOI.

ACKNOWLEDGEMENTS

• Nothing to declare

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Received: January 08, 2025
Accepted: July 24, 2025
JEL Classification: C24, I32, J43

Editor de seção: Gustavo Inácio de Moraes

APPENDIX. RESULTS OF THE REGRESSIONS USING DATA FROM THE 2017-2018 POF - Dependent Variable: lnrendt from each occupational sector

Table A1 - Estimation Results of Equation 5 - Nutrient Calories

Dependent Variable: lnrendt from each occupational sector

Sector	Agricultural	Non-Agricultural	Self-Employment	Other Jobs
Estimation Method	**IV-2SLS**	**IV-2SLS**	**OLS**	**OLS**
Lncalorie	16.52 (0.048)	11.32 (0.015)	0.22 (0.720)	-2.43 (0.631)
lncalorie²	-1.16 (0.052)	-0.812 (0.014)	0.002 (0.951)	0.19 (0.601)
Edumother	-	-	0.020 (0.059)	0.05 (0.052)
Childten	-	-	-0.02 (0.772)	-0.07 (0.690)
eduhead	0.07 (0.000)	0.07 (0.000)	0.04 (0.000)	0.03 (0.248)
Lnagehead	-	3.27 (0.155)	0.73 (0.912)	19.99 (0.502)
lnagehead²	-0.08 (0.278)	-0.33 (0.302)	-0.10 (0.923)	-3.01 (0.498)
Lnadulm	0.31 (0.007)	0.27 (0.003)	0.30 (0.050)	0.30 (0.508)
Lnadulf	0.11 (0.397)	0.256 (0.008)	0.31 (0.047)	0.22 (0.608)
lnsizehous	-	-	0.06 (0.762)	-0.27 (0.676)
Lnpcereals	-1.35 (0.003)	-0.58 (0.039)	-0.25 (0.539)	1.88 (0.162)
Lnpbeans	3.14 (0.000)	2.51 (0.000)	1.52 (0.014)	0.71 (0.682)
Lnpoil	-0.83 (0.101)	-0.40 (0.240)	-0.73 (0.121)	-2.70 (0.108)
Lnpsugar	0.16 (0.046)	-0.03(0.134)	0.15 (0.084)	-0.33 (0.376)
Lnpmilk	-0.39 (0.119)	-0.26 (0.879)	-0.13 (0.532)	0.03 (0.971)
lnrainfal	-	-	0.07 (0.368)	0.21 (0.313)
Dlocal	0.53 (0.012)	-	0.48 (0.264)	1.56 (0.355)
m0	0.36 (0.163)	0.02 (0.909)	0.22 (0.454)	-0.10 (0.891)
m1	-0.13 (0.035)	0.04 (0.529)	-0.05 (0.737)	-0.55 (0.399)
m2	0.22 (0.060)	-0.07 (0.125)	0.23 (0.276)	0.53 (0.518)
m3	0.05 (0.135)	0.02 (0.453)	0.01 (0.846)	-0.14 (0.211)
Cons	-52.35(0.073)	-44.06(0.007)	3.17 (0.753)	-19.08 (0.615)
	Nº obs.= 923	Nº obs.= 1149	N º obs.= 421 R^2 =0.35	Nº obs.= 66 R^2 = 0.65
White Test:			Prob > Chi²=0.0740	Prob > Chi²=0.4421
Pagan-Hall Test:	Prob > Chi²= 0.9978	Prob > Chi²= 0.9380		
Sargan's Test:	Prob > Chi² = 0.5012	Prob >Chi²= 0.0914		
Instrumented:	lncalorie lncalorie²	lncalorie lncalorie²		

Source: Results constructed by the authors.

Note: p-Value in parentheses.

Table A2 - Estimation Results of Equation 5 – Vitamin B1

Dependent Variable: lnrendt from each occupational sector

Sector	Agricultural	Non-Agricultural	Self-Employment	Other Jobs
Estimation Method	**OLS**	**IV-2SLS**	**OLS**	**OLS**
lnvitB1	0.09 (0.031)	-0.56 (0.017)	-0.01 (0.878)	0.02 (0.939)
lnvitB1²	-0.03 (0.187)	-0.40 (0.016)	-0.07 (0.006)	-0.04 (0.797)
Edumother	0.02 (0.027)	-	0.02 (0.053)	0.05 (0.063)
Childten	-0.12 (0.012)	-	-0.04 (0.542)	-0.09 (0.063)
eduhead	0.06 (0.000)	0.06 (0.000)	0.03 (0.000)	0.03 (0.277)
Lnagehead	3.56 (0.589)	4.15 (0.057)	0.50 (0.940)	15.66 (0.540)
lnagehead²	-0.55 (0.575)	-0.46 (0.131)	-0.05 (0.957)	-2.41 (0.532)
Lnadulm	0.21 (0.072)	0.22 (0.013)	0.29 (0.059)	0.27 (0.541)
Lnadulf	0.13 (0.240)	0.23 (0.012)	0.32 (0.041)	0.11 (0.787)
lnsizehous	0.15 (0.367)	-	0.06 (0.773)	-0.19 (0.785)
Lnpcereals	-1.38 (0.000)	-0.62 (0.022)	-0.43 (0.285)	1.72 (0.206)
Lnpbeans	3.00 (0.000)	2.17 (0.000)	1.70 (0.006)	0.93 (0.599)
Lnpoil	-1.15 (0.001)	-0.85 (0.008)	-0.64 (0.172)	-2.67 (0.122)
Lnpsugar	0.12 (0.054)	0.12 (0.041)	0.17 (0.059)	-0.36 (0.317)
Lnpmilk	-0.17 (0.338)	-	-0.18 (0.381)	-0.02 (0.983)
lnrainfal	0.05 (0.382)	-	0.06 (0.423)	0.18 (0.382)
Dlocal	0.62 (0.063)	-	0.45 (0.298)	1.37 (0.353)
m0	0.35 (0.116)	0.02 (0.935)	0.15 (0.601)	0.02 (0.974)
m1	-0.15 (0.250)	0.03 (0.633)	-0.05 (0.751)	-0.45 (0.438)
m2	0.25 (0.115)	-0.10 (0.006)	0.21 (0.332)	0.43 (0.546)
m3	0.001(0.985)	0.02 (0.329)	0.01 (0.766)	-0.11 (0.309)
Cons	-1.16 (0.912)	4.15 (0.231)	4.57 (0.644)	-18.76 (0.626)
	Nº obs.= 923	Nº obs.= 1149	Nº obs.= 421 R^2 =0.35	Nº obs.= 66 R^2 = 0.65
White Test:	Prob > Chi^2=0.9956		Prob > Chi^2=0.1373	Prob > Chi^2=0.4421
Pagan-Hall Test:		Prob > Chi^2=0.7035		
Sargan's Test:		Prob > Chi^2=0.0938		
Instrumented:		lnvitB1 lnvitB1²		

Source: Results constructed by the authors.
Note: p-Value in parentheses.

Table A3 - Estimation Results of Equation 5 – Vitamin B2

Dependent Variable: lnrendt from each occupational sector

Sector	Agricultural	Non-Agricultural	Self-Employment	Other Jobs
Estimation Method	**OLS**	**IV-2SLS**	**OLS**	**OLS**
lnvitB2	0.21(0.000)	-1.05 (0.34)	0.03 (0.724)	-0.07 (0.786)
lnvitB2²	-0.001 (0.965)	-0.61 (0.029)	-0.07 (0.058	0.04 (0.807)
Edumother	0.02 (0.028)	-	0.02 (0.077)	0.05 (0.053)
Childten	-0.11 (0.025)	-	-0.02 (0.704)	-0.16 (0.339)
eduhead	0.06 (0.000)	0.07 (0.000)	0.03 (0.001)	0.03 (0.308)
Lnagehead	0.92 (0.888)	-	0.46 (0.944)	30.11 (0.276)
lnagehead²	-0.17 (0.863)	0.16 (0.002)	-0.06 (0.956)	-4.51 (0.277)
Lnadulm	0.23 (0.050)	0.46 (0.001)	0.28 (0.060)	0.13 (0.787)
Lnadulf	0.12 (0.284)	0.22 (0.058)	0.31 (0.049)	0.003 (0.995)
lnsizehous	0.20 (0.233)	-	0.06 (0.752)	-0.33 (0.604)
Lnpcereals	-1.40 (0.000)	-0.63 (0.059)	-0.48 (0.238)	1.66 (0.221)
Lnpbeans	2.94 (0.000)	1.84 (0.000)	1.81 (0.003)	0.95 (0.591)
Lnpoil	-1.19 (0.001)	-1.07 (0.018)	-0.58 (0.213)	-3.10 (0.069)
Lnpsugar	0.12 (0.048)	0.17 (0.031)	0.17 (0.063)	-0.29 (0.428)
Lnpmilk	-0.17 (0.325)	0.12 (0.543)	-0.14 (0.513)	0.16 (0.827)
lnrainfal	0.06 (0.255)	-	0.06 (0.418)	0.15 (0.494)
Dlocal	0.55 (0.096)	-0.17 (0.418)	0.46 (0.283)	1.94 (0.214)
m0	0.33 (0.141)	-0.10 (0.640)	0.15 (0.619)	0.23 (0.769)
m1	-0.11 (0.415)	0.08 (0.212)	-0.06 (0.716)	-0.67 (0.265)
m2	0.22 (0.165)	-0.12 (0.273)	0.21 (0.320)	0.69 (0.355)
m3	0.001 (0.986)	0.003 (0.917)	0.01 (0.848)	-0.08 (0.463)
Cons	3.46 (0.742)	2.12 (0.291)	4.33 (0.661)	-41.01 (0.328)
	Nºobs.= 923	Nº obs.= 1149	Nº obs.= 421 R^2=0.35	Nº obs.=66 R^2=0.65
White Test:	Prob > Chi^2=0.9933		Prob > Chi^2=0.1095	Prob > Chi^2=0.4421
Pagan-Hall Test:		Prob > Chi^2=0.9982		
Sargan's test:		Prob > Chi^2=0.1066		
Instrumented: l	*nvitB2 lnvitB2²*			

Source: Results constructed by the authors.
Note: p-Value in parentheses.

Table A4 - Estimation Results of Equation 5 – Vitamin A

Dependent Variable: lnrendt from each occupational sector

Sector	Agrícultural	Non-Agricultural	Self-Employment	Other Jobs
Estimation Method	**OLS**	**IV-2SLS**	**OLS**	**OLS**
lnvitA	0.09 (0.161)	2.13 (0.034)	0.13 (0.144)	-0.13 (0.720)
lnvitA^2	0.003 (0.643)	-0.25 (0.041)	-0.01 (0.481)	0.01 (0.804)
Edumother	0.02 (0.017)	-	0.02 (0.068)	0.05 (0.049)
Childten	-0.13 (0.006)	-	-0.04 (0.519)	-0.17 (0.398)
eduhead	0.06 (0.000)	0.06 (0.000)	0.03 (0.000)	0.03 (0.266)
Lnagehead	3.60 (0.579)	19.11 (0.033)	1.94 (0.770)	24.87 (0.322)
lnagehead^2	-0.56 (0.561)	-2.76 (0.043)	-0.29 (0.773)	-3.76 (0.323)
Lnadulm	0.19 (0.099)	0.21 (0.179)	0.29 (0.055)	0.15 (0.752)
Lnadulf	0.10 (0.381)	0.18 (0.209)	0.28 (0.070)	0.05 (0.902)
lnsizehous	0.13 (0.414)	-0.41 (0.168)	0.03 (0.867)	-0.25 (0.688)
Lnpcereals	-1.46 (0.000)	-	-0.36 (0.378)	1.99 (0.155)
Lnpbeans	3.01 (0.000)	1.77 (0.000)	1.65 (0.008)	0.61 (0.738)
Lnpoil	-1.30 (0.000)	-	-0.71 (0.134)	-2.94 (0.082)
Lnpsugar	0.12 (0.042)	0.04 (0.682)	0.15 (0.103)	-0.31 (0.396)
Lnpmilk	-0.04 (0.842)	-0.06 (0.785)	-0.15 (0.492)	0.13 (0.864)
lnrainfal	0.05 (0.371)	-	0.07 (0.331)	0.15 (0.480)
Dlocal	0.59 (0.074)	1.22 (0.047)	0.57 (0.193)	1.75 (0.234)
m0	0.38 (0.086)	0.11 (0.693)	0.23 (0.428)	0.09 (0.908)
m1	-0.14 (0.286)	-0.42 (0.075)	-0.09 (0.566)	-0.63 (0.286)
m2	0.25 (0.118)	0.47 (0.122)	0.28 (0.191)	0.60 (0.397)
m3	0.01 (0.847)	0.02 (0.519)	0.01 (0.841)	-0.09 (0.388)
Cons	-1.46 (0.888)	31.40 (0.022)	2.35 (0.814)	-32.19 (0.386)
	Nº obs.= 923	Nº obs.= 1149	Nº obs.= 421 R^2 =0.34	Nºobs.= 66 R^2 = 0.65
White Test:	Prob > Chi^2=0.9994		Prob > Chi^2=0.07	Prob > Chi^2=0.4421
Pagan-Hall Test:		Prob > Chi^2 = 1,00		
Sargan's Test:		Prob > Chi^2 = 0.4600		
Instrumented:		lnvitA lnvitA^2		

Source: Results constructed by the authors.
Note: p-Value in parentheses.

Table A5 - Estimation Results of Equation 5 – Nutrient: Iron

Dependent Variable: lnrendt from each occupational sector

Setor	Agricultural	Non-Agricultural	Self-employment	Other Jobs
Estimation Method	**IV-GMM**	**IV-2SLS**	**OLS**	**OLS**
Lniron	2.62 (0.032)	4.33 (0.033)	0.16 (0.170)	-0.21 (0.799)
lniron²	-0.72 (0.044)	-1.23 (0.032)	-0.002 (0.968)	0.10 (0.670)
Edumother	-	-	0.02 (0.061)	0.04 (0.066)
Childten	-	-	-0.03 (0.628)	-0.08 (0.602)
eduhead	0.06 (0.000)	0.06 (0.000)	0.04 (0.000)	0.03 (0.245)
Lnagehead	-	-	0.89 (0.893)	21.84 (0.530)
lnagehead²	-0.04 (0.629)	0.14 (0.014)	-0.12 (0.905)	-3.28 (0.523)
Lnadulm	0.34 (0.003)	0.37 (0.005)	0.30 (0.050)	0.27 (0.560)
Lnadulf	0.17 (0.124)	0.27 (0.034)	0.30 (0.056)	0.16 (0.703)
lnsizehous	-	-	0.06 (0.757)	-0.27 (0.691)
Lnpcereals	-1.47 (0.000)	-1.01 (0.016)	-0.35 (0.394)	1.89 (0.160)
Lnpbeans	3.05 (0.000)	2.86 (0.000)	1.62 (0.009)	0.65 (0.712)
Lnpoil	-0.97 (0.031)	-0.65 (0.134)	-0.64 (0.172)	-2.69 (0.112)
Lnpsugar	0.18 (0.012)	0.16 (0.066)	0.16 (0.078)	-0.35 (0.334)
Lnpmilk	-0.28 (0.255)	0.16 (0.488)	-0.01 (0.651)	0.01 (0.994)
lnrainfal	-	-	0.07 (0.347)	0.21 (0.329)
Dlocal	0.43 (0.012)	-0.02 (0.926)	0.49 (0.262)	1.651 (0.367)
m0	0.26 (0.349)	0.05 (0.839)	0.20 (0.504)	-0.10 (0.901)
m1	-0.10 (0.048)	0.11 (0.164)	-0.06 (0.713)	-0.59 (0.421)
m2	0.17 (0.085)	0.02 (0.880)	0.24 (0.271)	0.56 (0.528)
m3	0.04 (0.217)	0.01 (0.762)	0.01 (0.839)	-0.13 (0.245)
Cons	3.15 (0.248)	-2.13 (0.436)	3.70 (0.711)	-29.44 (0.592)
	Nº obs. = 923	Nº obs.= 1149	Nº obs.= 421 R^2 = 0.34	Nº obs.=66 R^2 = 0.65
White Test:			Prob > Chi^2 = 0.1509	Prob > Chi^2 = 0.4421
Pagan-Hall Test:	Prob > Chi^2 = 0.9991	Prob > Chi^2 =1.0		
Sargan's Test:		Prob > Chi^2 = 0.2398		
Hansen J statistic:	Prob > Chi^2 = 0.8352			
Instrumented:	lniron lniron²	lniron lniron²		

Source: Results constructed by by the authors.
Note: p-Value in parentheses.