Food Security (2025) 17:345–361
https://doi.org/10.1007/s12571-025-01523-x

RESEARCH ARTICLE

Diet quality rather than caloric intake associated with labour wages in Kenya

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Received: 28 December 2023 / Accepted: 29 January 2025 / Published online: 12 March 2025

Abstract
Malnutrition, in all its forms, poses a significant threat to human development and economic growth. Consequently, enhancing food security and consumption is a moral and social imperative for fostering development. Despite the substantial evidence on the relationship between caloric intake and labour productivity, research on the connection between labour productivity and diet quality, measured by micronutrient intake, is scarce. This paper, focusing on Kenya, estimates the linkages between micronutrient intake and labour productivity, measured by household labour income. The daily intakes of energy and micronutrients per adult male equivalent at the household level is computed employing food consumption data collected in the 2015–2016 Kenya Integrated Household Budget Survey. Econometric results show that daily micronutrient (haem iron, zinc, folate, calcium, vitamins B2 and A) intakes are significantly and positively correlated with labour productivity. The quality of diets, reflected by micronutrient intakes, has a bigger impact on labour productivity than the daily energy consumed, measured by caloric intake. This paper contributes to the nutrition–productivity literature and provides a basis for designing policies to improve the nutritional quality of diets.

Keywords Micronutrient intakes · Labour productivity · Micro-econometric estimation · Kenya · Diet quality

1 Introduction

Malnutrition, in all its forms, can jeopardise human development and economic growth in different ways. Undernutrition is linked with an increased risk of infectious diseases (Walson & Berkley, 2018), while overweight and obesity are risk factors for cardiovascular diseases, diabetes and other chronic diseases (Kearns et al., 2014). The adverse effects of ill health on wages and productivity in low-income contexts is well described in the literature (Strauss & Thomas, 1998). Moreover, undernutrition in early childhood significantly affects neurocognitive development (Kar et al., 2008), with long-term consequences for learning abilities (Case & Paxson, 2008) and years of schooling (Victora et al., 2008). These cognitive and educational deficits can have a lasting impact on labour productivity and earning potential in adulthood (Galasso & Wagstaff, 2019; Hanushek & Woessmann, 2008; Hoddinott et al., 2008).

Recent global reports highlighted the prevalence of malnutrition in all its forms across the world. As reported by the

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FAO latest report (*The State of Food Security and Nutrition in the World 2024*, 2024), in 2022, approximately 45 million children under five years (6.8%) suffered from acute malnutrition, while 148 million children (22.3%) experienced chronic malnutrition. Additionally, the prevalence of anaemia among women aged 15–49 increased from 28.5% (520 million) to 29.9% (571 million). The prevalence of obesity among adults has increased from 12.1% (591 million) in 2012 to 15.8% (881 million). These statistics underscore the significance of malnutrition, whether in the form of undernutrition, micronutrient deficiencies, or overnutrition, as a pressing global health and development issue. A common factor contributing to all forms of malnutrition is an imbalanced diet characterized by inadequate or excessive consumption of macronutrients and/or micronutrients. The consumption of macronutrients (carbohydrates, proteins and fats) has a direct impact on caloric intake and energy balance, whereas micronutrients (vitamins and minerals) are essential for maintaining health, promoting growth, and preventing disease. Micronutrients deficiencies can hinder growth, lead to specific diseases, and exacerbate both infectious and chronic conditions (Tulchinsky, 2010).

The discourse on nutrition and productivity has primarily focused on caloric malnutrition. The nutrition-based efficiency wage hypothesis (Leibenstein, 1957) suggests that increased nutrient intake, particularly caloric intake, enhances productivity and boosts wages in low-income populations. This hypothesis has guided the majority of research on nutrition and productivity (Strauss, 1986). Nevertheless, research based on this hypothesis produced mixed results. Numerous studies have found a positive correlation between caloric intake and productivity (Deolalikar, 1988; Haddad & Bouis, 1991; Immink & Viteri, 1981), while others reported no significant effect on nutrition (Ayalew, 2003; Berha et al., 2021) or even contradictory results (Ayalew, 2003; Weinberger, 2004).

In contrast, recent research indicate that diet quality, defined by the nutritional content and diversity of food consumed, plays an equally important role as caloric intake for determining individuals' productivity levels (Berha et al., 2021). While less common, studies on diet quality reveal that enhanced dietary diversity and nutrient-rich diets have a positive impact onlabour productivity. For example, improved diet quality had a greater impact on productivity for low-consumptions households in Ethiopia (Berha et al., 2021). Likewise, studies in India demonstrated that inadequate iron intake is associated with lower wages, with potential wage increasing ranging from 5 to 17% when recommended iron intake levels are met (Weinberger, 2004). In Thailand, increased consumption of calcium, vitamin A and iron has been linked to higher household earnings and farm output, whereas caloric intake only contributes to higher farm output (Tiwasing et al., 2019). These case studies in Asia and Africa suggest that both caloric intake and diet quality play a crucial role in enhacing labour productivity and economic outcomes.

Within this context, Kenya, situated on the eastern coast of sub-Saharan Africa, encounters substantial challenges related to food security and nutrition. Malnutrition, encompassing both undernutrition (with 10% of the children under five being underweight) and overnutrition (with 3% of the children under five being overweight), remains a concern. Factors such as persistent food insecurity, inadequate dietary quality (only 31% of children aged 6–23 months are fed a minimum acceptable diet) and limited access to safe drinking water and sanitation exacerbate these challenges (Kenya National Bureau of Statistics & The DHS Program ICH, 2023). In light of these issues, Kenya presents a pertinent case for investigating the relationship between diet quality, caloric intake, and labour productivity. Although recent studies focused on improving caloric and macronutrient intake (Ramos et al., 2020; 2022; Nechifor et al., 2021) there is limited research on micronutrient intake and its effects.

This paper aims to investigate the relationship between labour productivity and both caloric and micronutrient intakes in Kenya. This study expands the scope of the nutrition-based efficiency wage hypothesis by incorporating a more comprehensive understanding of diet, including micronutrient intake and dietary diversity, and by analysing the entire economy, rather than solely focusing on the agricultural sector, which has been the primary focus of much of previous research.

The remainder of the paper is organised as follows. Section 2: Material and Methods presents the study population, the data sources and the micro-econometric models used to estimate the contributions of nutrients to labour productivity applicable to the Kenyan context. Section 3: Results and Discussion presents and comments the findings and limitations. Finally, Sect. 4: Conclusion summarizes the key insights and implications of the study.

2 Material and methods

2.1 Population

Kenya has a rapidly growing population that today stands at around 53 million. While the rural areas still host a substantial share of the population, urban centres have been experiencing rapid growth (the share of the urban population was 28% in 2020 compared with 19.9% in 2000) (UN Population Division, 2018). Nairobi and Mombasa are the main cities, with populations of around 4.4 million and 1.2 million, respectively (Kenya National Bureau of Statistics, 2019). This urbanisation trend has implications for food security and dietary patterns, as urban and rural areas face different challenges in terms of access to affordable and nutritious diets.

The proportion of the population living on less than USD 3.65 a day (in 2017 purchasing power parity) and chronically vulnerable due to poor nutrition, food insecurity and preventable diseases was 70% in 2021. Agriculture is an important component of the economy, contributing approximately 21.2% of Kenya's gross domestic product in 2022. Although the country's per capita gross domestic product is among the largest on the African continent, the country suffers from large economic inequalities (United Nations Children's Fund, 2022).

2.2 Data sources

2.2.1 Kenya integrated household budget survey

The main data source for this analysis is the 2015–2016 Kenya Integrated Household Budget Survey (KIHBS) from the Kenya National Bureau of Statistics (2018). This survey collected detailed data on 21 773 households regarding, for example, demographic characteristics, education, health and disability of household members; total income; income from different sources including (dependent and independent) labour income of household members; total and specific food expenditure; and quantity of food consumed at home by food item during the last 7 days at the household level. Only data regarding the 73% of the surveyed households that report income from a labour source are used in this analysis, even though the survey covers different sources of income at the household level. The survey is spatially referenced at the county level, distinguishing between rural and urban counties; 58% of the chosen sample is composed of rural households (versus 42% urban households), and 57% of the sample households have at least one skilled worker among their economically active members. To ensure the accuracy of the analysis, outliers in monthly wages per adult male equivalent (AME) and in daily food quantities consumed per item per AME were identified and addressed. Specifically, outliers were detected using the median absolute deviation method (Leys et al., 2013) and treated accordingly, ensuring that the results reflect a more accurate and reliable representation of the data.

2.2.2 Food composition tables

The 2018 Kenya food composition table helped to convert the reported food consumption into nutrients. This table provides information on the energy, macronutrient (protein, fat, carbohydrate) and micronutrient (calcium, iron, vitamins, etc.) content of food items consumed in Kenya, allowing for the calculation of nutrient consumption when combined with the food quantities consumed in each household (Food and Agriculture Organization of the United Nations and Government of Kenya, 2018).

To match the nutrient contents in the food composition table with the consumed food items collected in the KIHBS we used the Kenya Nutrients Conversion Table (NCT). The methodology for its construction is detailed in Moltedo et al. (2021).

2.3 Outcome variable

The outcome variable is monthly labour income, which serves as proxy for labour productivity. Monthly labour income is derived from the 'Wages and salary during the last month (basic salary)' variable in the KIHBS. This variable captures the income earned through formal and informal labour activities. Labour income is measured at the household level, representing the total income from all economically active members within the household. To ensure comparability across households, the total monthly labour income is computed on a per AME basis. This calculation adjusts for differences in household composition, accounting for the age and sex of household members. Although this measure of labour income includes wages from both formal, dependent work and informal, autonomous labour, it does not capture income derived from children's contributions or non-remunerated family workers. However, it is considered an appropriate and practical proxy for overall labour productivity at the national level, particularly when the focus is not on a single sector (such as agriculture) but on a broad measure of productivity.

2.4 Explanatory variables

The explanatory variables in the model include households' daily caloric intake and a set of micronutrient intakes per AME. Additionally, proxies for food security, health and education of economically active household members are included as controlled variables to a better adjustment of the estimated equation. These factors are considered important as food insecurity, poor health and low education are closely associated with inadequate nutrition and low labour productivity. Risk factors for low labour productivity are also associated with poor nutrition. The outcome and explanatory variables are listed in Table 1. In the following paragraphs, we provide a detailed description of the explanatory variables, organized by relevant categories, to illustrate how each factor contributes to the model.

2.4.1 Nutrient intake

The model considers caloric intake (measured as daily energy consumption (DEC) per AME) and micronutrient as the key variables for nutrient intake. The DEC represents

Table 1 Summary of descriptive statistics (outcome and explanatory variables)

Variables	Mean	Standard deviation	Minimum	Maximum
Wage AME (KES/month/AME)	61 049	84 850	123	1 613 999
ln (Wage AME)	10.37	1.19	4.81	14.29
DEC AME (kcal/day/AME)	2 628	1 138	0	10 410
ln (DEC AME)	7.77	0.537	1.89	9.25
Calcium (mg/day/AME) (*)	825.86	534.6	0	5 698
Total iron (mg/day/AME) (*)	25.5	14.5	0	155
Non-haem iron (mg/day/AME)	23.6	13.9	0	146
Haem iron (mg/day/AME)	1.9	2.262	0	39.88
Zinc (mg/day/AME) (*)	17.61	16.99	0	493.82
Folate (mg/day/AME)	958.49	647.5	0	7 429.52
Vitamin A RAE (µg /day/AME) (*)	559.46	847.99	0	17 859
Vitamin C (mg/day/AME) (*)	129.72	117.66	0	1 369
Vitamin B_2 (mg/day/AME) (*)	1.8	1.37	0	30.04
Vitamin B_{12} (µg /day/AME) (*)	4.55	6.71	0	100.28
FIES raw score	3.84	3.13	0	8
Severe food insecurity (FIES)	0.31	0.46	0	1
University education (proportion)	0.11	0.27	0	1
Secondary education (proportion)	0.29	0.35	0	1
Primary education (proportion)	0.47	0.41	0	1
Chronic disease and disability (number)	2.16	1.39	0	14

(*) The estimated average requirements per day per adult male (19–50 years) are 1 000 mg for calcium, 6 mg for total iron, 9.4 mg for zinc, 320 mg for folate, 625 µg for vitamin A RAE, 75 mg for vitamin C, 1.1 mg for vitamin B_2 and 2 µg for vitamin B_{12} (Institute of Medicine, National Academies, 2006).

Source: Authors' own calculations.

the total daily energy intake from all foods consumed by household members, adjusted for age, sex, and household size. The micronutrient intake variables include the daily intake per AME of 10 micronutrients relevant for public health: calcium, haem iron from animal sources, non-haem iron from non-animal sources, folate, zinc, and the following vitamins: A (expressed as retinol activity equivalents (RAEs)), B1, B2, B12, and C.

The model does not include macronutrient intakes as they have already been thoroughly examined in previous studies (Moltedo et al., 2021; Ramos et al., 2022). Furthermore, given the high correlation between the consumed quantities of macronutrients, caloric intake, and micronutrient intake (see Table 3 in the annex), we chose to exclude them from the models to avoid redundancy and potential collinearity.

To calculate nutrient intake, the first step is to convert food quantities to nutrient quantities (see Sect. 2.2.2 'Food composition tables'). Food quantity consumed per day per AME outliers were detected for each food item using the median absolute deviation method (Moltedo et al., 2021; Ramos et al., 2022) and replaced by the median food quantity consumed per day per AME per item at the county level (Leys et al., 2013). We then approximated the individual micronutrient intake by computing the daily consumption of each micronutrient per AME (Weisell & Dop, 2012). For consistency, all variables in the analysis are expressed per day and per AME.

A preliminary collinearity check of each of the 10 micronutrients with the daily energy consumption (DEC) and with the rest of the micronutrients revealed that vitamin B1 is highly correlated with total iron and DEC; the same holds for total iron and non-haem iron, which are correlated with DEC (see Table 3 in the annex). Following previous literature (Dormann et al., 2013; Shrestha, 2020; Young, 2017), we consider there exists high correlation and potential collinearity problems when coefficients are higher than 0.7. Consequently, we removed vitamin B1, non-haem iron and total iron from the multivariable econometric model to ensure the absence of collinearity problems. Nevertheless, they were included in the bivariate analysis.

The paper also tests for correlations between each micronutrient and the rest of the explanatory variables (Food Insecurity Experience Scale (FIES), education, and disease and disability) as well as correlations among the micronutrients themselves. All correlations yielded Pearson values below 0.7.

2.4.2 Food security, education and sociodemographic variables

This study employs the Food Insecurity Experience Scale (FIES) as a proxy for food insecurity. The FIES is a metric of food insecurity severity that relies on people direct yes/no responses to eight brief questions regarding their access to adequate food.[1] The FIES is also one of the indicators of Sustainable Development Goal 2. Based on the responses, different variables can be constructed, such as a raw score ranging from 0 to 8, where 0 indicates no food insecurity and 8 represent the most severe form. Following guidelines of the Food and Agriculture Organization of the United Nations (FAO) (Cafiero et al., 2018), we computed an indicator of severe food insecurity based on dummy variables that groups categories 7 and 8 of the score and uses category 0 as the reference.[2]

The education variable represents the highest level of formal education attained by economically active household members. It is constructed by determining the maximum level of education (primary, secondary or university) reached by each economically active household member aged between 15 and 65 years. We then calculated the proportion of economically active household members with each maximum level of formal education.

The other sociodemographic variables used to construct the model are household size (number of people living in the household) and demographic composition (sex and age of all household members). These variables were included as part of the explanatory variables in the model and were essential for expressing consumption variables on a per AME basis.

2.4.3 Disease and disability variable

The disease and disability variable is a composite measure that captures both disability and chronic diseases among household members. It is based on two self-constructed indicators: (1) one that accounts for disability (e.g. visual, hearing, speech, physical, mental) of any household members and (2) another that accounts for chronic diseases (e.g. diabetes, cancer, blood pressure, hypertension) among economically active household members (aged between 15 and 65 years). The disease and disability variable brings together the numbers computed in each of these indicators, thus capturing the number of household members with a disability and the number of economically active household members with chronic diseases.

[1] More information about the FIES can be found at https://www.fao.org/in-action/voices-of-the-hungry/using-fies/en/.

[2] Detailed procedures can be found in the FAO technical document *Modelling Food Insecurity in Bivariate and Regression Analyses*.

2.5 Empirical strategy and statistical analysis

Based on the empirical evidence that shows a positive relationship between food consumption and labour productivity, we estimated this relationship in the case of Kenya – for the whole economy and by differentiating between rural and urban areas and between skilled and unskilled labour households. The food consumption variables are the caloric and micronutrient daily intakes per AME.

The empirical literature employs two variables to measure labour productivity: production and wages. Production is generally used when labour productivity is measured for a particular sector of activity and when labour markets are not suited to the use of wages as a proxy for labour productivity. Where production is utilised, the sectoral production function is estimated to measure the direct impact of nutrition on the sectoral output. This impact is calculated through a function of labour efficiency whose contributing factors are, among other household characteristics, nutrient intakes.

The level of analysis is national, and it is assumed that the labour market is competitive (in line with the nutrition–earning literature). Consequently, labour productivity is estimated through the semi logarithmic wage equation at the household (h) level (Tiwasing et al., 2019) (Eq. (1)):

$$\begin{aligned} lnW_{AMEh} &= \alpha_h + \beta_{1h} lnDEC_{AMEh} + \beta_{2n,h} NUT_{AMEn,h} \\ &\quad + \beta_{3h} FIES_h + \beta_{4e,h} EDUC_{e,h} + \beta_{5h} D \wedge D_h + \mu \end{aligned} \tag{1}$$

where W_{AME} corresponds to the monthly dependent and independent labour earnings reported per AME at the household (h) level, on which we apply a natural logarithm transformation. The same transformation is applied to the DEC_{AME}, which is the daily energy (kilocalories) consumed per AME at the household level; NUT_{AME} refers to each micronutrient (minerals and vitamins) intake per day per AME at the household level. $FIES_h$ represents the Food Insecurity Experience Scale, an indicator of food insecurity experiences at the household level. $EDUC$ refers to the maximum level of formal education reached by the household's economically active members, and the variable $D \wedge D$ corresponds to the number of economically active members in a household with chronic diseases and/or disability. Finally, μ is the disturbance term with the usual properties.

We estimated Eq. (1) considering all households with $W_{AMEh} > 0$ at the national level, differentiating between rural and urban households and between households with skilled or unskilled workers. The definition of rural or urban household is given by the KIHBS. Households are defined as skilled when they have at least one economically active member with a secondary education degree and as unskilled when none of the economically active household members has completed secondary education.

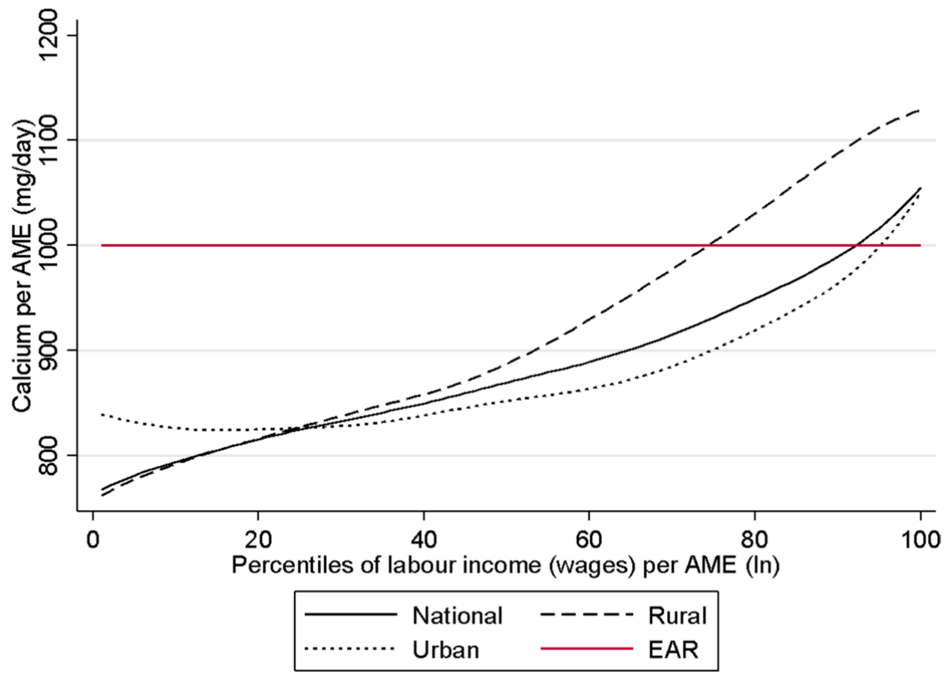


Fig. 1 Calcium intake per AME across percentiles of labour income per AME at the household level. NB: The EAR for calcium is 1 000 mg/day for an adult male (Institute of Medicine, National Academies, 2006). *Source:* Authors' own calculations

We performed descriptive statistics of all the model variables and run bivariate analysis between the outcome variable and the covariates, and non-parametric regressions of the nutrient variables across percentiles of household labour income (wage) per AME (in natural logarithm). In the final step, we built stepwise multivariable econometric models for the whole sample, stratified by rural/urban households and skilled/unskilled households.

3 Results and discussion

3.1 Descriptive statistics

The descriptive statistics of the variables introduced in the model consider the observations for which the wage per AME is > 0 (Table 1). The mean wage per AME is KES 61 049, equivalent to USD 604, by considering an average USD/KES exchange rate of 101 for the period 2015–2016. The mean caloric intake is 2 628 kcal per day per AME, which is higher than the 2 206 kcal per day per capita estimated by the FAO[3] but lower than the 2 892 kcal per day per AME estimated for an adult population in Nairobi (Vila-Real et al., 2022).

The mean values of micronutrient intakes are below or above the estimated average requirements (EARs) for an adult male (19–50 years) that we used as the reference (Institute of Medicine, National Academies, 2006), depending on the micronutrient of interest. Calcium and vitamin A mean intakes are below the reference, while the mean consumptions of zinc, folate and water-soluble vitamins (vitamins C, B_2 and B_{12}) are above. In the case of iron, although mean consumption seems to be above the EARs for adult males, the interpretation is not so straightforward, as the EARs for adult females are double those for adult males and there are no specific recommendations for the haem and non-haem forms.

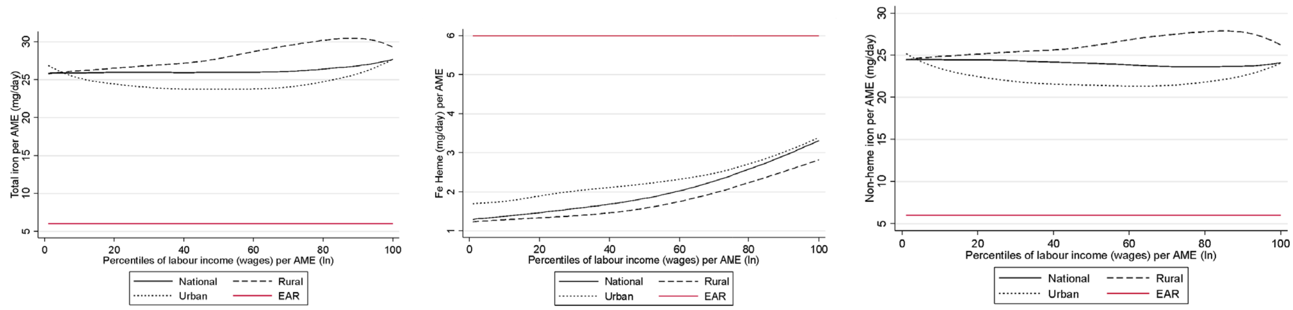
All the micronutrients except non-haem iron show a significant and positive association with ln (Wage AME) in the bivariate analysis, and most of them have a p-value of < 0.0001 (see Table 4 in the annex).

3.2 Bivariate analysis between labour income and micronutrients: non-parametric regressions

Figures 1, 2, 3, 4 show the mean intake of selected micronutrients[4] per day per AME across the percentiles of labour income per AME (both at the household level). Red lines represent the reference values of EARs for adult males (Institute of Medicine, National Academies, 2006). We focus first on calcium intake.

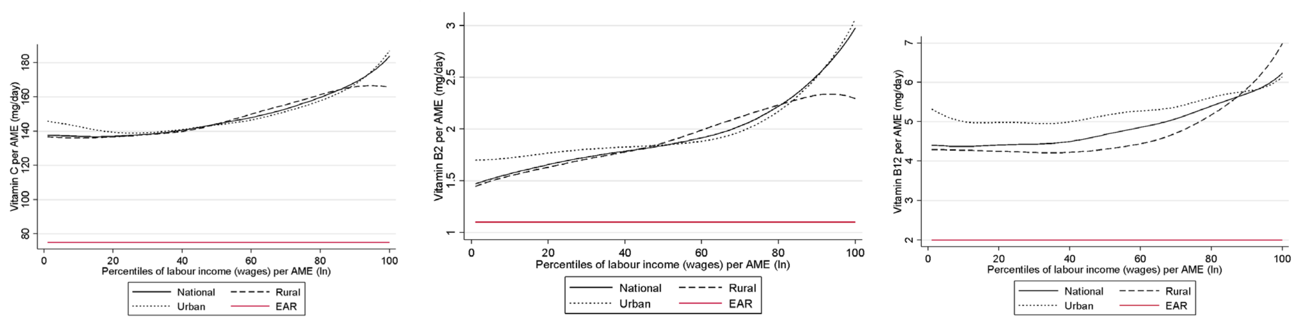
[3] FAOSTAT is available at http://www.fao.org/faostat.

[4] Zinc and folate mean consumption values are not presented in graphs. Both are well above the reference values and show similar distributions.



(a) Total iron (b) Haem iron (c) Non-haem iron

Fig. 2 Iron (total, haem and non-haem) intake per AME across percentiles of labour income per AME at the household level. NB: The EAR for iron is 6 mg/day for an adult male (Institute of Medicine, National Academies, 2006). *Source:* Authors' own calculations



(a) Vitamin C (b) Vitamin B_2 (c) Vitamin B_{12}

Fig. 3 Water-soluble vitamin (vitamins C, B_2, B_{12}) intake per AME across percentiles of labour income per AME at the household level. NB: The EARs for vitamins C, B_2 and B_{12} are 75 mg/day, 1.1 mg/day and 2 µg /day for an adult male, respectively (Institute of Medicine, National Academies, 2006). *Source:* Authors' own calculations

As labour income per AME increases, so does the consumption of calcium per AME. However, only households with a labour income above the 70th percentile in rural areas and above the 90th percentile in urban areas meet the daily calcium requirement. Rural households show higher calcium intakes than urban ones (Fig. 1).

In relation with iron, the mean of (total) intake increases with higher labour income per AME. It is above the EAR for all households surveyed, with higher intakes among the rural population (Fig. 2, panel a). However, a detailed analysis of the sources of iron shows a different picture. On the one hand, the haem iron (dietary iron obtained from animal sources) intakes are below the total iron EAR for all households surveyed, with increased intakes for households with higher labour incomes and for urban populations on average (Fig. 2, panel b). On the other hand, all households have non-haem iron (dietary iron obtained from plant foods) intakes above the iron EAR. Furthermore, there is a marked difference between rural and urban populations in non-haem iron intake. There is a lower intake (Fig. 2, panel c) and a less direct increase with higher labour income among the urban households.

Similarly, the daily zinc intakes per AME also increase with the percentiles of labour income per AME. The rural–urban gap in zinc intakes is only remarkable in low percentiles of labour income (with higher intakes among the urban population), although all households seem to have an intake of zinc well above the EAR (See Fig. 5 in the annex).

In contrast with the behaviour of the other micronutrients, the intake of all the water-soluble vitamins in the model (vitamins C, B_2, $B_{12,}$ and folate) is above the EARs. Overall, vitamins C, $B_{2,}$ and B_{12} have higher intake values

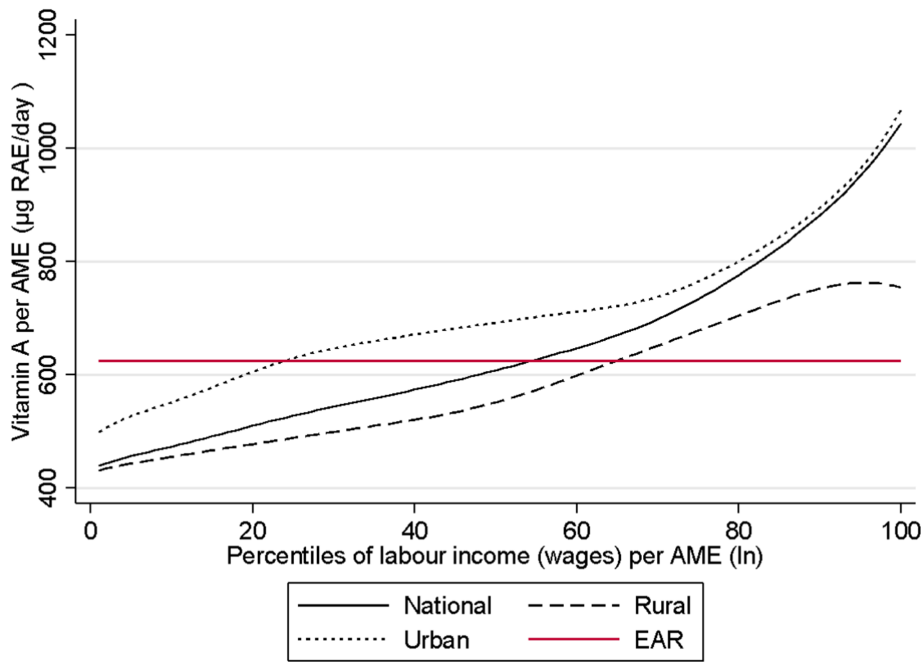


Fig. 4 Lipid-soluble vitamin (vitamin A) intake per AME across percentiles of labour income per AME at the household level. NB: The EAR for vitamin A is 625 µg RAE/day for an adult male (Institute of Medicine, National Academies, 2006). *Source:* Authors' own calculations

among the highest percentiles of labour income (Fig. 3, panels a, b and c). However, the patterns are different for the rural and urban populations. The rural and urban estimates of vitamin C intake are almost identical, although urban populations are estimated to have higher intakes in the low and high extremes of the labour income distribution (Fig. 3, panel a). The pattern for vitamin B_2 shows higher values among the urban population within the low and high percentiles of labour income and higher values for the rural population in the middle of the distribution of labour income (Fig. 3, panel b). Vitamin B_{12} intakes are higher among the urban populations in most parts of the labour income distribution. Only in the highest percentiles of labour income does the rural population's consumption become higher (Fig. 3, panel c). Folate intake is higher at both extremes of the labour income distribution (lowest and highest wages) in urban populations but lower in the middle percentiles. For rural populations, folate intake increases with labour income up to the 90th percentile after which it declines (Fig. 6 in the annex).

The intakes of nutrients above the EARs observed are an expected result. Household survey data collected by household consumption and expenditure surveys typically produce, for the whole population, higher estimates of average nutrient consumption than those obtained from individual-level data (Karageorgou et al., 2018).

For the mean consumption of the lipid-soluble vitamin A, expressed as RAEs, the pattern is similar to that of the other micronutrients in relation to labour income, with increased intake among the households in the high percentiles of the labour income distribution. The average intakes of vitamin A are higher for the urban population throughout the whole distribution (Fig. 4).

The results show a higher intake of soluble vitamins (vitamin C, B2 and folate), and non-haem iron (all of them more commonly found in plant food) among the rural population. People living in urban areas show a higher intake of vitamins A and B12 and minerals such as zinc and haem iron that are mainly found in animal-source foods. This is consistent with the current pattern of diets in the rural/urban environments of many African countries, where food of animal origin is more accessible to (and consumed by) the urban population than to the rural population (Miller et al., 2022).

Finally, caloric and nutrient daily intakes are higher for this sample population than the estimates for the whole KIHBS sample analysed in Moltedo et al. (2021). The direct association between wages and daily intakes of calories and nutrients may be associated with the fact that the subsample of households used in this research meet the criterion of having reported a non-zero wage income.

Furthermore, the above figures are consistent with the results obtained in the bivariate regressions conducted in the construction phase of the model (see Table 4 in the annex). All micronutrient variables (except non-haem iron) and the daily caloric intake show a positive and significant bivariate association with ln (Wage AME), at the national level and within the strata studied (rural/urban, skilled/unskilled).

3.3 Labour productivity and nutrients relationship: multivariable regression estimates

After describing the features of micronutrients intake in Kenya, this section presents the results of the regression exercise. First, when the micronutrient variables are introduced in the econometric model, the logarithm of the daily energy consumed, ln (DEC AME), is negatively associated with the dependent variable (the logarithm of labour income – ln (Wage AME)) or loses its significance as in the rural model (see Table 2). This finding is consistent with other results available in the literature. For example, Tiwasing et al. (2019) analyse the impact of energy and micronutrient consumption on labour productivity measured by earnings and report a positive relationship of labour productivity with micronutrient intakes but a negative association with energy intake (Tiwasing, 2016). In addition, Weinberger (2004) examines the impact of iron intake on agricultural labour productivity, measured by wages, in India, and reports a positive impact of micronutrient intake but a negative impact in relation to energy consumption per AME.

These apparently contrasting results (i.e. the impact of micronutrient consumption versus energy consumption) may reflect the importance of micronutrients in a high-quality diet in contrast with so-called empty calories, which provide high energy but little micronutrient content.

Table 2 Nutrition, Education and Health estimates for Labour Productivity in Kenya

	ln (Wage AME)				
Variables	National	Unskilled	Skilled	Rural	Urban
ln (DEC AME)	−0.154***	−0.127***	−0.168***	0.0131	−0.154***
	(0.0235)	(0.0336)	(0.0330)	(0.0373)	(0.0297)
Calcium (mg/day/AME)	8.54e-05**	0.000266***	−5.70e-05	0.000142***	8.65e-05
	(3.45e-05)	(0.0000567)	(4.55e-05)	(4.75e-05)	(5.65e-05)
Haem iron (mg/day/AME)	0.0753***	0.0558***	0.0964***	0.0457***	0.0692***
	(0.00643)	(0.00946)	(0.00724)	(0.00792)	(0.00748)
Zinc (mg/day/AME)	0.00313***	0.00362***	0.00274***	0.00247***	0.00223***
	(0.000602)	(0.00113)	(0.000697)	(0.000751)	(0.000802)
Folate (mg/day/AME)	3.81e-05**	1.76e-06	6.40e-05***	2.70e-05	1.81e-05
	(1.84e-05)	(2.90e-05)	(2.39e-05)	(2.42e-05)	(2.71e-05)
Vitamin B2 (mg/day/AME)	0.0465***	0.0359*	0.0446***	0.0621***	0.0349***
	(0.00959)	(0.0217)	(0.0105)	(0.0195)	(0.0108)
Vitamin A RAE (μg/day/AME)	4.21e-05**	−8.53e-06	6.70e-05***	2.13e-05	7.39e-05***
	(1.74e-05)	(3.13e-05)	(1.74e-05)	(2.43e-05)	(2.00e-05)
Vitamin C (mg/day/AME)	−0.000722***	−0.000767***	−0.000672***	−0.000750***	−0.000634***
	(0.000116)	(0.000168)	(0.000160)	(0.000142)	(0.000214)
Vitamin B12	−0.0142***	−0.0188***	−0.0115***	−0.0183***	−0.0129***
(μg /day/AME)	(0.00241)	(0.00387)	(0.00315)	(0.00328)	(0.00347)
Severe food insecurity (FIES) (Q7 and Q8)	−0.453***	−0.432***	−0.470***	−0.411***	−0.433***
	(0.0205)	(0.0278)	(0.0300)	(0.0243)	(0.0337)
University education (proportion)	1.156***	-	−0.0509***	0.879***	0.917***
	(0.0452)		(0.00834)	(0.0638)	(0.0768)
Secondary education (proportion)	0.566***	-	0.863***	0.243***	0.487***
	(0.0371)		(0.0940)	(0.0450)	(0.0719)
Primary education (proportion)	0.199***	0.203***	0.164*	0.0253	0.228***
	(0.0343)	(0.0383)	(0.0923)	(0.0384)	(0.0724)
Chronic disease and disability (number)	−0.0957***	−0.136***	−0.0509***	−0.0535***	−0.107***
	(0.00631)	(0.0119)	(0.00834)	(0.00791)	(0.00982)
Constant	11.28***	11.15***	11.10***	9.850***	11.71***
	(0.172)	(0.244)	(0.256)	(0.273)	(0.225)
Observations	15,890	6,838	9,052	9,277	6,613
R2	0.186	0.093	0,219	0,126	0,164

NB: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' own estimation.

We tested this hypothesis by introducing the consumption of carbohydrates (the main dietary source of empty calories) in the models and observed that the negative sign was picked up by carbohydrate consumption while daily energy consumed retained its positive sign. This is in line with findings from Tiwasing (2016), who observes that an increase in the consumption of grains and starches reduces income, whereas extra consumption of meat and poultry, fruits, vegetables and nuts lead to an increase in income.

Furthermore, this finding may enrich the efficiency wage hypothesis proposed by Leibenstein (1957) and further developed by Strauss (1986). As previously mentioned, this hypothesis considers that better nutrition amplifies farm labour productivity as measured by wages and/or output. This hypothesis is widely accepted by researchers despite some studies find no association or a negative one between the two variables. Among the reasons for these discrepancies may be the indicators used to proxy nutrition; in most of cases, caloric intake has been used, but anthropometric indicators, nutrient consumption or diet quality indicators have also been used (Berha et al., 2021). In addition, the outcome used to measure labour productivity may have an impact on these results, as in the study of Tiwasing et al. (2019). In that study, which was conducted in rice farms in Thailand, labour productivity measured by earnings was inversely related to caloric intake when micronutrients were introduced in the model, but that was not the case when the outcome was farm output. For farm output, both micronutrients and caloric intake were positively associated with productivity in the multivariable model (Tiwasing et al., 2019).

Moving to micronutrients, the econometric analysis carried out highlights that there is an undoubted positive association between micronutrients and labour productivity. All explanatory variables are significant at the 1% significance level in the national model, and most of them are also significant, although at lower significance levels, in the other sub-models (see Table 2). Iron from animal sources turns out to be the most important micronutrient, among those considered, in all model specifications. In particular, a unit increase in the daily haem iron intake per AME generates a 0.075% increase in the household labour earning (proxy of labour productivity) in the national model. These results are aligned with the findings from Weinberger (2004) and Tiwasing et al. (2019). Also, the association between labour income and two of the water-soluble vitamins (vitamins B12 and C) changes direction when introduced in the model. These two vitamins show a positive impact on labour income when introduced alone or in combination with energy consumption but their sign changes when other micronutrients are introduced. These variations are consistent throughout the five models studied and should be further explored.

The other covariates introduced in the model behaved as expected. Households with higher shares of members completing all of primary, secondary and university education have higher levels of productivity than those with lower shares. The association between schooling and worker productivity has been shown in other African contexts (Burger & Teal, 2015), and a recent report by UNESCO conducted in eight Sub-Saharan countries highlighted that education is associated with positive employment, especially when it comes to returns to schooling (Rouane & Suárez-Robles, 2022).

The lower productivity in households with higher disability or disease burdens aligns with results from another study in Kenya showing that having a disability was associated with lower labour market participation (Bechange et al., 2024). Also, a study on chronic diseases and labour productivity in South Africa concluded that diabetes was significantly associated with reduction in labour force participation among women (Ekholuenetale et al., 2023), and a broader study on health burden and labour productivity in Africa (including 45 African countries) showed that a 1% increase in health burden would reduce labour productivity by 17% in the low-income economy (Mobosi et al., 2022).

Finally, greater severity of households' food insecurity, measured by the FIES, was negatively associated with labour income in the bivariate and multivariable models, adjusted by all other covariates. This suggests that experiencing severe limitations in access to adequate food is associated with lower labour wages independently of the level of education or disease and disability in the household. The association between food insecurity and labour productivity has been shown in other rural contexts of Africa like Madagascar (Okoye et al., 2017), or Nigeria (Adepoyu & Obialo, 2022). Moreover, a study analysing wage-setting policies and food insecurity in 139 countries highlights the circularity of this association where wage-setting policies are seen as an important intervention for addressing the risks of food insecurity among low-income workers (Reeves et al., 2021).

Nevertheless, the fact that the association between micronutrients and labour wages remains significant when these variables are introduced in the model suggests that the positive effect of micronutrient consumption on labour productivity is independent of the education level, the disease/disability or the food insecurity status of the household.

3.4 Discussion of limitations

As in all modelling endeavours, there are caveats. Firstly, the single-period survey (2015–2016) available for Kenya only allows for a cross-sectional exercise and limits the possibility of establishing a trend in the association. Nevertheless, the literature offers other studies showing short- and long-run causalities with applications to other sub-Saharan countries with time series (Raji, 2020) or panel data (Berha et al., 2021) analyses. Secondly, we cannot rule out the risk of endogeneity in the estimation. Tiwasing et al. (2019) and Berha et al. (2021) mention the possibility of choosing instrumental variables in a two-stage least squares estimation; however, none of the surveys' variables (households' characteristics) appears to be a valid instrument to improve estimation results. Finally, the variable chosen as the proxy of labour productivity – that is, monthly labour earnings per AME at the household level – has some limitations. It does not enable the labour productivity of household members who did not report remuneration for their labour (e.g. work done by children) to be captured. However, it has the advantage of allowing for a labour productivity measure for overall economic activities and not exclusively for a particular economic sector. Most research that uses household surveys to measure the link between food security and nutrition and labour productivity focuses on the agricultural sector (Berha et al., 2021; Tiwasing et al., 2019), using its sectoral production function to estimate labour productivity. Moreover, we can only extrapolate these results to households with at least one member earning a labour income, as only households with reported labour wages were included in the model.

4 Conclusions

Employing relevant econometric techniques, this study takes a step forward in understanding the relationship between micronutrient intake and labour productivity in wage-earning households in Kenya. A key finding is that calcium, haem iron, folate, zinc, vitamin B2 and vitamin A have an unambiguously positive impact on labour productivity, even when adjusted by daily caloric intake, household food insecurity, education level, and disease and disability status. The importance of a nutritious diet is also highlighted by the larger effect on labour productivity of a micronutrient-rich diet than the consumption of diets higher in calories but poor in micronutrients.

This emerging paradigm shift highlights the importance of not only meeting caloric requirements but also ensuring a balanced and varied diet to support optimal cognitive and physical functioning.

Given the current high prevalence of micronutrient deficiencies across the Kenyan population affecting mostly children under five years and women of reproductive age, this study underscores the need for Kenya policymakers to prioritize micronutrient interventions. Addressing these deficiencies could not only reduce morbidity and mortality but also enhance labour productivity and improve the overall well-being of the population. Improving diets quality could also contribute to the achievement of Sustainable Development Goals 2 (Zero Hunger) and 8 (Decent Work and Economic Growth), where labour productivity plays a key role.

Both central and local governments should implement targeted strategies and policies to better understand and mitigate micronutrient deficiencies. In the short term, efforts should focus on strengthening data collection on nutrition and health to increase the current evidence, while promoting the supplementation, and consumption of micronutrient-rich foods. In the long-term, strategies should be aimed at dietary diversification, food fortification and broader public health measures.

Currently, the Government of Kenya put in place four strategies to prevent, control and manage micronutrient deficiencies: dietary diversification, food fortification, micronutrient supplementation, and disease prevention measures. These measures include controlling parasitic infections, improving water, sanitation and hygiene (WASH), and providing health education and counselling. The study highlights haem iron as the most critical micronutrient for labour productivity. This finding further justifies the need to expand fortification programmes, such as those already in place since 2006, which has been developed under the Ministry of Health, Republic of Kenya (2018). However, better coordination is needed between the public and private sectors. The public sector should provide resources for basic research and create a supportive legislative environment for food fortification, while the private sector should invest in expanding production and distribution capacities within the country.

The study's findings hold when applied to different subsamples, though there is some variation between rural and urban populations; thus, policies must be tailored to the specific needs of both. Policymakers should also work to improve the availability of more granular data related to health, nutrition and food security to better inform future interventions.

Appendix 1

Table 3 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) DEC	1																	
(2) Calcium	0.649	1																
(3) Iron	**0.854**	0.635	1															
(4) Haem iron	0.428	0.497	0.374	1														
(5) Non-haem iron	**0.827**	0.587	**0.989**	0.235	1													
(6) Zinc	0.515	0.426	0.499	0.352	0.468	1												
(7) Folate	**0.700**	0.475	**0.743**	0.284	**0.734**	0.493	1											
(8) Vitamin C	0.444	0.636	0.489	0.233	0.476	0.309	0.377	1										
(9) Vitamin B1	**0.883**	0.518	**0.860**	0.357	**0.845**	0.491	**0.823**	0.369	1									
(10) Vitamin B2	0.598	0.579	0.531	0.401	0.493	0.407	0.559	0.362	0.521	1								
(11) Vitamin A (RAE)	0.293	0.332	0.286	0.434	0.232	0.251	0.302	0.269	0.262	0.373	1							
(12) Vitamin B12	0.299	0.623	0.276	0.629	0.191	0.237	0.193	0.224	0.237	0.285	0.569	1						
(13) FIES (raw)	−0.126	−0.156	−0.088	−0.184	−0.064	−0.158	−0.135	−0.100	−0.067	−0.226	−0.126	−0.019	1					
(14) FIES (Q7&Q8)	−0.116	−0.154	−0.091	−0.144	−0.073	−0.132	−0.127	−0.108	−0.064	−0.196	−0.104	−0.020	0.816	1				
(15) University education	0.070	0.112	0.053	0.206	0.023	0.126	0.083	0.089	0.021	0.187	0.116	0.070	−0.255	−0.198	1			
(16) Secondary education	−0.001	0.081	0.025	0.048	0.019	0.050	0.035	0.096	−0.027	0.058	0.054	0.027	−0.177	−0.172	−0.157	1		
(17) Primary education	0.008	0.000	0.056	−0.126	0.079	−0.043	0.016	0.058	0.042	−0.074	−0.063	0.003	0.153	0.107	−0.383	−0.539	1	
(18) Chronic Diseases & Disability	−0.252	−0.212	−0.189	−0.158	−0.173	−0.162	−0.190	−0.172	−0.188	−0.167	−0.115	−0.122	−0.013	−0.025	−0.033	0.063	−0.031	1

Source: Authors' own estimation

Note: dietary variables are in daily intakes per AME

Table 4 Bivariate regressions

Variables	National ln(WageAME)																
ln(DEC AME)	0.144***																
	(0.0209)																
Calcium		0.000284***															
(mg/day/AME)		(1.85e-05)															
Haem iron			0.112***														
(mg/day/AME)			(0.00700)														
Non-Heme Iron				0.000599													
(mg/day/AME)				(0.000695)													
Total Iron					0.00326***												
(mg/day/AME)					(0.000670)												
Folate						0.0002288***											
(µg /day/AME)						(0.000015)											
Zinc							0.0105***										
(mg/day/AME)							(0.000944)										
Vitamin B1								0.0363***									
(mg/day/AME)								(0.00896)									
Vitamin B_2									0.169***								
(mg/day/AME)									(0.0100)								
Vitamin B_{12}										0.0141***							
(µg /day/AME)										(0.00166)							
Vitamin A RAE											0.000179***						
(µg /day/AME)											(1.89e-05)						
Vitamin C												0.000686***					
(mg/day/AME)												(9.18e-05)					
Severe food insecurity (FIES)													– 0.710***				
(Q7Q8)													(0.0200)				
University education														1.262***			
(proportion)														(0.0334)			
Secondary education															0.422***		
(proportion)															(0.0261)		
Primary education																– 0.523***	
(proportion)																(0.0233)	
Chronic disease																	– 0.103***
and disability (number)																	(0.00672)
Constant	9.252***	10.14***	10.16***	10.36***	10.29***	10.15***	10.19***	10.30***	10.07***	10.31***	10.27***	10.28***	10.59***	10.23***	10.25***	10.62***	10.60***
	(0.163)	(0.0178)	(0.0154)	(0.0191)	(0.0195)	(0.0172)	(0.0187)	(0.0204)	(0.0200)	(0.0118)	(0.0136)	(0.0147)	(0.0108)	(0.00987)	(0.0124)	(0.0148)	(0.0179)
Observations	15,890	15,891	15,891	16	16	16	15,891	16	15,891	16	15,891	15,891	15,891	15,891	15,891	15,891	15,891
R^2	0.004	0.016	0.045	0.000	0.002	0.0155	0.022	0.001	0.038	0.006	0.016	0.005	0.076	0.079	0.016	0.032	0.015

NB: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Source: Authors' own estimation.

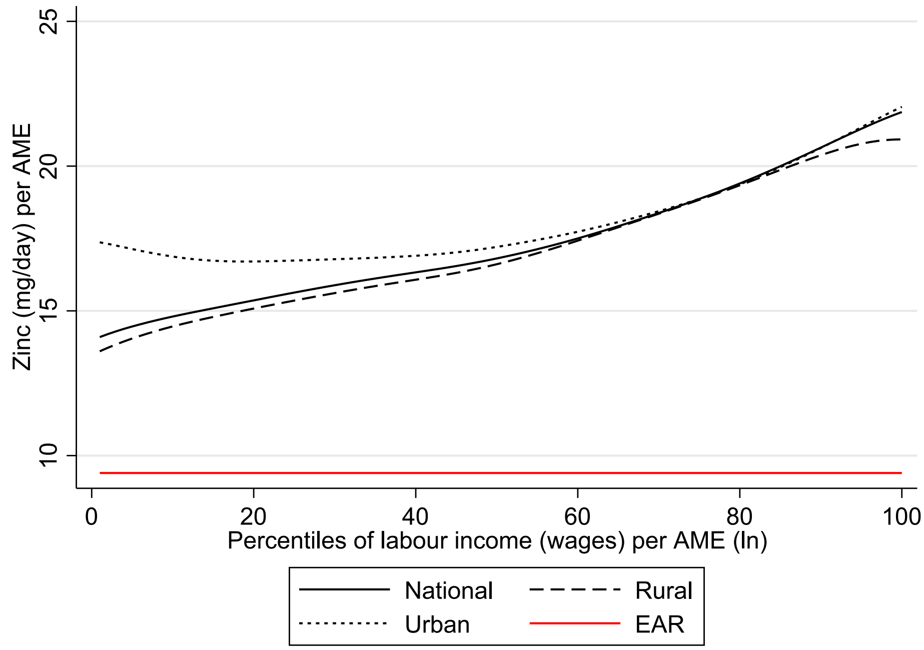


Fig. 5 Zinc intake per AME across percentiles of labour income per AME at the household level. NB: The EAR for zinc is 9.4 mg/day for an adult male (Institute of Medicine, National Academies, 2006). *Source*: Authors' own calculations

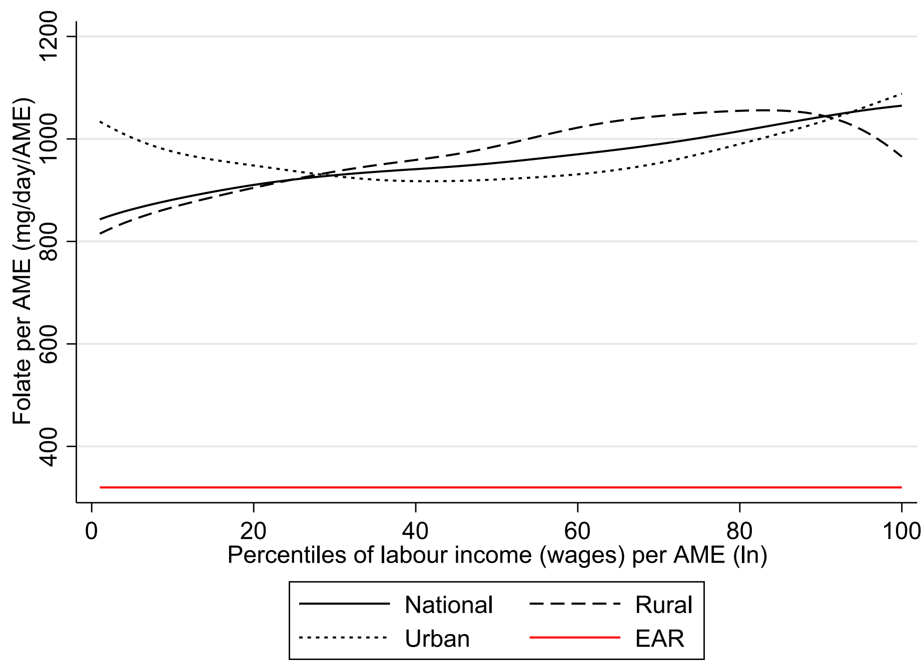


Fig. 6 Folate intake per AME across percentiles of labour income per AME at the household level. NB: The EAR for folate is 320 mg/day for an adult male (Institute of Medicine, National Academies, 2006). *Source*: Authors' own calculations

Acknowledgements The authors are grateful to the editor and the anonymous reviewers for their constructive comments on previous versions of this manuscript. We thank Lara Cockx & Ole Boysen (European Commission JRC, Seville) for their comments and suggestions to improve the paper.

Funding The authors did not receive support from any organization for the submitted work.

Data Availability The Kenya Integrated Household Budget Survey (KIHBS) is available upon request from the Kenya National Bureau of Statistics. The Kenya Nutrients Conversion Table is publicly available on Respisalud at https://hdl.handle.net/20.500.12105/25905.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

Disclaimer The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

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