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The contribution of agricultural inputs in reducing child stunting

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Abstract

While the impact of agricultural inputs on crop yields has received considerable attention, their influence on nutritional outcomes has been somewhat neglected. This study aims to fill this gap by examining the role of agricultural inputs in mitigating child stunting through linear dynamic panel regressions conducted at the country level. By analysing data from approximately half of the world's countries over a 20-years period, our findings reveal that mineral fertilizers make significant positive contributions to reducing child stunting. Other agricultural inputs, such as per-capita agricultural land and manure exhibit a positive contribution in reducing child stunting, but their statistical significance is obtained only in few models. Surprisingly, irrigation appears to have no impact on alleviating child stunting.

Keywords Agricultural inputs, Environmental impact, Linear dynamic panel, Child stunting

JEL classification Q01, Q15, Q18

Introduction

With an estimated 691 to 783 million individuals suffering from hunger in 2022, food security remains a pressing concern for approximately 9.2% of the global population [12]. This situation has been exacerbated by the adverse effects of the Covid-19 pandemic and subsequent geopolitical instability, such as the Russo-Ukrainian war, leading to an increase of 122 million people experiencing hunger between 2019 and 2022. The lowest percentage was recorded in 2017, with approximately 7.6% of the world population affected by hunger [12]. Thus, despite decades of steady decline, hunger is on the rise instead of further reduction. Moreover, considering that nearly 2 billion additional individuals will require food by 2050, according to United Nations projections [32], it is evident that food security will be a critical challenge in the coming decades.

This imperative to increase food production intersects with another pressing need of our time: reducing greenhouse gas (GHG) emissions and, more broadly, environmental pressure [17]. Agriculture serves as the nexus where these conflicting demands converge. Agriculture, including animal husbandry, is the primary driver of food production, yet it is estimated that agriculture, forestry, and other land uses contribute to approximately 24% of total global greenhouse gas emissions [16]. Activities such as deforestation, tillage, and fertilizer use all emit GHGs [16]. Different agricultural practices and inputs yield varying production outcomes and environmental impacts. Therefore, making optimal choices regarding their combination and intensity necessitates a clear assessment of their benefits and costs.

Environmental costs have been extensively studied, with research by Jones and Sands [18] and Laborde et al. [19] investigating the impact of agricultural productivity gains and subsidies on global greenhouse gas (GHG) emissions, respectively. Conversely, the manifold benefits of agriculture have also been thoroughly examined. As a

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vital economic activity, agriculture provides income to farmers and contributes to national GDP. For instance, McArthur and McCord [23] explore the effects of agricultural inputs on cereal productivity and subsequent GDP growth resulting from such productivity gains. However, the primary function of agricultural production, and its most significant and direct benefit, is to provide nutrition.

While much attention has been devoted to the relationship between agricultural inputs and productivity, typically measured as yield per unit of input, nutritional outcomes are a more intricate phenomenon than mere food quantity. Though authors such as Fuglie [14] have extensively researched agricultural productivity, few have delved into the direct link between agricultural inputs and nutrition. Some progresses have been made by investigating the connection between agricultural productivity and dietary outcomes, as seen in the work of Mughal and Fontan Sers [25]. However, scant attention has been paid to the direct impact of agricultural inputs on nutrition, aside from evaluations of specific programmes targeting agricultural inputs, such as fertilizer subsidies, which often lack generalizability.

This study aims to address this gap by examining the effect of various agricultural inputs on child stunting, adopted as a proxy of undernourishment. Drawing on a large panel of countries spanning 20 years and utilizing data from the Food and Agriculture Organization of the United Nations (FAO) and the World Bank, our findings indicate that mineral fertilizers significantly contribute to reducing child stunting, with approximately a 0.15–0.2 percentage points decrease for each kilogram per hectare of combined N–P–K. While per-capita land and manure also appear to decrease child stunting, their effects are statistically less robust, and irrigation appears to have no impact.

The next section provides a short literature review on the role of agricultural inputs, Sect. "Data and methods" describes the data and methods used for the analysis, while Sect. "Results and discussion" presents the results, discusses them and provide their policy implications. Finally, Sect. "Conclusions" is devoted to conclusions.

Literature review

Production typically carries adverse environmental consequences, consuming natural resources and often generating harmful by-products. Agricultural production is no exception, exerting significant stress on the environment. Beyond land and water usage, crucial natural resources, agricultural production contributes to greenhouse gas emissions through land use, exacerbated by the production and utilization of mineral fertilizers, which account for approximately 2.1% of global CO_2 emissions [24]. Pesticides also pose environmental concerns, causing negative externalities such as the reduction of insect populations [29] and soil microbiological activity [36]. Consequently, increasing land productivity often entails environmental costs. However, it also allows to reach a certain level of production using less land, thus accruing environmental benefits.

Effective decision-making regarding the optimal utilization of agricultural inputs necessitates a comprehensive cost–benefit analysis considering environmental externalities alongside agriculture's primary objective of providing nutrition to the global population. Numerous studies focus on the role of agricultural inputs in enhancing productivity and subsequently impacting other economic indicators. For example, McArthur and McCord [23] explore the relationship between inputs and cereal yields, finding a significant positive correlation, further revealing that a half-ton increase in staple yields correlates with a 14 to 19% rise in GDP, as corroborated by Evenson and Gollin [11]. Enhanced agricultural productivity has been associated with poverty reduction by scholars such as De Janvry and Sadoulet [10] and Christiaensen et al. [8].

While some researchers investigate macroeconomic indicators like GDP and poverty reduction [8, 10, 23], others concentrate on more direct outcomes, such as nutrition. In imperfect markets, where production and consumption decisions are intertwined, agricultural productivity can directly influence dietary outcomes [30]. For instance, Mughal and Fontan Sers [25] find that a one percent increase in cereal yields reduces undernourishment by 0.84% in South Asia, echoing the findings of Shankar et al. [30] regarding nutritional outcomes and land productivity gains in the same region. However, Shankar et al. [30] lament the lack of clear evidence linking agricultural inputs and nutrition, noting only relatively strong evidence of the positive impact of livestock on dietary aspects, especially child growth.

Walls et al. [33] conduct a review focusing on nutritional outcomes and agricultural input subsidies rather than the inputs themselves, emphasizing the importance of agricultural productivity for food security and examining the effects of subsidies on this relationship. Despite finding some positive effects of input subsidy programmes on nutritional outcomes, they also highlight a limited literature on the topic, often confined to specific countries, and suggest that input subsidies may even exacerbate food diversification issues. Similarly, Berti et al. [6] review a broader category of agricultural interventions, finding only partial and often modest positive effects on nutritional outcomes.

An aspect that has been better examined is the relation between trade, particular trade of agricultural commodities, and nutritional outcomes. Results, however, have been very mixed and contradictory. Mary [21], for example, looks at the effect of free trade on undernourishment, finding that a greater degree of trade openness is associated to a higher prevalence of undernourishment. With regard to obesity, instead, the opposite seems to hold, with Mary and Stoler [22] finding that trade liberalization helps to reduce it in developing countries. The result of Mary [21] is in sharp contrast with Marson et al. [20], that find a positive role of trade openness, particularly of cereal trade, in reducing undernourishment. It worth to mention that, according to this last paper, the beneficial effect of trade openness in limiting the rate of malnutrition is not due to an income effect of trade but rather on the impact of imports, especially of cereals, on other determinants of food security: e.g. food availability.

Income is another important aspect that has received attention for its impact on nutritional outcomes. If it seems almost obvious its role in reducing undernourishment, despite also this fact has found some critiques by, among others, Wolfe and Behrman [37] and Behrman and Wolfe [5], its impact on obesity and other forms of malnutrition is under debate. Salois et al. [27] find that elasticities of several nutrients, e.g. calories, proteins and, particularly fats, are decreasing in income levels thus implying that low-income countries are likely to experience an increasing share of fats in their citizens' diets along their growth path. In their meta-analysis, despite finding a significant heterogeneity of estimates, Santeramo and Shabnam [28] confirm a stronger income elasticity for fat and micronutrients compared to calories and proteins, thus corroborating the fears of Salois et al. [27]. The higher elasticity of a detrimental nutrient such as fat has also some positive implications, such as a high sensitivity to marked based policy interventions, as evidenced by Abay et al. [1].

Given the mixed evidence and the reliance on national micro-data in several studies, which limits its result generalizability, this paper seeks to adopt a broader perspective on the relationship between agricultural inputs and nutrition. Although a country-level analysis sacrifices precision and data quality, it offers the best, and perhaps only, means of obtaining a comprehensive understanding of this relationship. Covering approximately half of the world's countries over a 20-year period (2001–2020), this study employs a linear panel data models, namely difference and system generalized method of moments (GMM) to assess the effects of various agricultural inputs on child stunting, controlling for factors such as per-capita GDP. Through this approach, the paper aims to provide a robust and general estimate of the impact of agricultural inputs on a proxy of undernourishment such as child stunting.

Data and methods

The analysis is conducted at the country level, encompassing all countries for which data are available. The focus is placed on the role of agricultural inputs on nutrition and, particularly, on reducing extreme cases of malnutrition. This last is a very broad and diversified phenomenon encompassing almost antithetical symptoms such as undernourishment and obesity. The analysis is limited to the first aspect that seems to be more impacted by agricultural production compared to obesity, for which cultural values and lifestyles have been found to be major determinants [9, 31].

Despite the availability of a direct measure of undernourishment, such as the percentage of undernourished persons over the whole population offered by FAO, another indicator has been chosen, namely the percentage of children under 5 years old suffering from stunting, with this being defined as: "low height-for-age. It is the result of chronic or recurrent under-nutrition, usually associated with poverty, poor maternal health and nutrition, frequent illness and/or inappropriate feeding and care in early life" [34]. The reason for this choice is that, while undernourishment necessitates nationally representative household surveys to be computed, child stunting is an anthropometric measure often routinely collected by schools or public health offices, as explained in this FAO document. The degree of data imputation, therefore, is likely to be far lower for the FAO indicator of child stunting rather than for the one of undernourishment. Other indicators, such as wasting, energy intake adequacy and the percentage of severely food insecure people have been discarded for the same reason or for paucity of observations. The percentage of children (5 years old or lower) suffering from stunting, together with all the agricultural related variables, have been retrieved from FAOSTAT, the statistical arm of FAO.

All the economic indicators, instead, are taken from the World Bank. Among these, there is constant (2017) per-capita GDP (*GDP_pc_PPP*) at power purchasing parity (PPP) and the total population of each country in each year (*Pop_tot*). In a second set of regressions, other economic controls are added, namely inflation rate (*Inflation_r*), gross capital formation (*Gross_cap_f*) and foreign direct investments (*FDI*). All of them are in per-capita terms, as shown in Table 1, and retrieved from the World Bank data portal.

The main regressors of interest are agricultural inputs, downloaded from FAOSTAT. Land is proxied by per-capita agricultural area (*Agr_area_pc*) and irrigation by the percentage of agricultural area equipped for irrigation

Table 1 Descriptive statistics

Variables	Mean	Std. dev.	Min.	Max.	N. obs.	Unit
Child_stunt	20.10	14.50	1.20	61.97	777	%
GDP_pc_PPP	15129	16121	683	108899	784	$ / person
GDP_pc_PPP2	488443	1142496	466	11859098	784	'000
Pop_tot	40697	125026	81	1382834	775	N / 1000
Agr_area_pc	1.78	4.93	0.01	52.67	775	ha / person
Irr_equip_perc	11.67	17.04	0.01	99.98	774	%
Manure_N_ph	16.36	34.53	0.08	286.78	775	Kg / ha
NPK_ph	51.13	74.38	0.00	435.06	765	Kg / ha
Pest_ph	2.88	5.86	0.00	41.94	775	Kg / ha
Conflict_deaths	0.53	2.51	0.00	25.83	768	N / pop. * 100K
N_droughts	0.13	0.21	0.00	1.00	616	N.
N_floods	1.08	1.50	0.00	14.00	763	N.
Agr_prod	410.22	289.50	31.68	1829.90	728	$ / 1000
FDI	370759	1531917	− 10823053	26572780	775	$ / 1000
Gross_cap_f	2064865	3432939	0	29239073	735	$ / 1000
Inf_rate	6.86	14.53	− 7.17	274.38	754	%

(*Irr_equip_perc*). Despite being less precise than the percentage of agricultural land under irrigation, also available from FAOSTAT, the scarcity of observations for this last variable has determined the choice of the former. As other crucial agricultural inputs, it is included the per-hectare summed quantity of nitrogen (N), phosphorus (P) and potassium (K) applied in soil (*NPK_ph*), the per-hectare quantity of agrochemicals (the sum of pesticides, insecticides and herbicides) (*Pest_ph*) and the quantity of N introduced in soil through manure (*Manure_N_ph*), also as per-hectare value. FAOSTAT further offers the number of tractors in use per country, a good proxy of mechanization, but this series has been discontinued since 2009 and has few observations. Therefore, a direct measure of agricultural productivity, namely the per-capita agricultural produced value (*Agr_prod*) is used as regressor, encompassing mechanization and other productivity enhancement factors such as knowledge accumulation. In fact, when considered in a regression at ceteris paribus levels of agricultural inputs, this regressor should capture all productivity gains not explained by the same considered inputs.

Finally, as controls for climate variability and conflicts, potentially important determinants of both agricultural productivity and malnutrition, three additional variables have been selected. The first two control for natural disasters, being the yearly number of floods (*N_floods*) and droughts (*N_droughts*), obtained from the EM-DAT dataset (The International Disaster Database). Despite the existence of several indicators that are potentially useful as meteorological–climatic controls, from simple average temperatures and precipitations to more elaborate indices such as the Palmer Severity Drought Index, these risks need to be scarcely meaningful when condensed at country-yearly level. A second problem is that the simple number of events is uninformative on their intensity, but the lack of information on this regard for a sufficient number of countries-years left the only option of using the selected variables as a second best. The number of casualties every hundred thousand persons caused by armed conflicts (*Conflict_deaths*) is the last control. Obtained from the Uppsala Conflict Data Program—UCDP, it includes casualties caused by international and domestic conflicts with or without the direct involvement of state entities. Basic statistics for all mentioned variables are reported in Table 1, while Fig. 2, in the Appendix, shows the correlation among the most important variables.

As a last remark, it has to be mentioned that, despite all variables being yearly values, with 21 years (2000–2020) of available data, the time periods have been reduced to 7 by taking 3 years averages for all variables: e.g. 2000–2002, 2003–2005, and so on. Given the persistency of a phenomenon such as malnutrition, a year-by-year analysis may be inappropriate returning results that are statistically not significant[1]. Despite some variations in the number of included countries in different models, 85 are usually represented. As visible in Fig. 1, that depicts in red the countries included in the analysis, they are mostly developing nations. Most of Western Europe, in fact,

[1] I thank an anonymous reviewer for suggesting to use three years averages instead of yearly values, for pointing at child stunting as a better alternative to undernourishment as dependent variable and for several other important suggestions, including the choice of the econometric models.

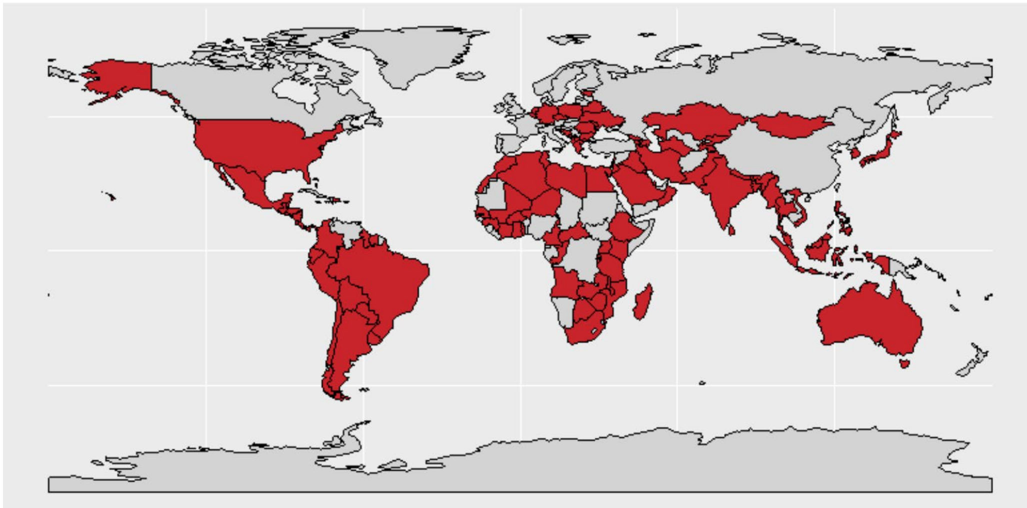

Fig. 1 Countries included in the analysis

is excluded for lack of data on the dependent variable. Given that undernourishment in high income countries is likely to be detached from agricultural productivity and mostly linked to distributional disparities, the underrepresentation of this category is possibly beneficial for the present analysis.

The model

Looking at the description of the difference and system generalized method-of-moments estimators as reported in Roodman [26], it is easy to see why they have been selected for the present analysis: "Both are general estimators designed for situations with *small T, large N* panels, meaning few time periods and many individuals; independent variables that are not strictly exogenous, meaning they are correlated with past and possibly current realizations of the error; fixed effects; and heteroskedasticity and autocorrelation within individuals". Proposed by Holtz-Eakin et al. [15], Arellano and Bond [3], Arellano and Bover [4] and Blundell and Bond [7], these are linear dynamic panel data models particularly useful in case of endogenous, or not strictly exogenous, regressors and paucity, or complete absence, of instruments other than the same regressors.

By having seven time periods (3 years averages over 21 years) and roughly 85 countries, the present case perfectly falls into the *small T, large N* situation mentioned in Roodman [26]. Furthermore, it is very likely that historical, institutional and past socio-economic conditions of countries play a role in determining the current overall nutritional status, therefore a model able to account for fixed effects is strongly advisable. The chosen economic controls, such as per-capita GDP, and the main regressors, namely the level of various agricultural inputs, are likely to be affected by nutritional outcomes. Abu-Fatima et al. [2], for example, estimates a loss of 2.6% of GDP in Sudan caused by malnutrition, of which 1.5 percentage points are attributable to reduced productivity. Finally, the persistent nature of malnutrition, or its slow pace of change, calls for a dynamic model, since past realizations of the dependent variable are likely to influence present ones. For all these reasons, the mentioned linear dynamic panel data models seem appropriate for the present case.

The model and its basic assumptions are now summarized by starting with a traditional linear dynamic panel model of the following type:

$$y_{i,t} = \gamma y_{i,t-1} \mathcal{B} X_{i,t} + \alpha_i + \epsilon_{i,t}, \qquad i = 1, 2, ..., n; \quad t = 2, 3, ..., T, \tag{1}$$

where $y_{i,t}$ is the ith observation of the dependent variable at time t, $y_{i,t-1}$ its lag with coefficient to be estimated γ, $X_{i,t}$ is a matrix of regressors and $\mathcal{B}$ a vector of associated coefficients to be estimated. For simplicity, we consider only regressors at time t, but lagged covariates can be added without altering the explanation. Similarly, past lags of the dependent variable, e.g. $t-2$, are also allowed together with eventual time dummies. The element α_i represents the time invariant characteristics of each ith unit of observation. Following Fritsch et al. [13], the model is based on these assumptions:

$$
\begin{aligned}
&\text{The data are independently distributed only across i,}\\
&E(\epsilon_{i,t})=0, \quad i=1,2,...,n; \quad t=2,3,...,T,\\
&E(\epsilon_{i,t}\cdot\alpha_i)=0, \quad i=1,2,...,n; \quad t=2,3,...,T,\\
&E(\epsilon_{i,t}\cdot\epsilon_{i,s})=0, \quad i=1,2,...,n; \quad t\neq s;\\
&E(y_{i,1}\cdot\epsilon_{i,t})=0, \quad i=1,2,...,n; \quad t=2,3,...,T,\\
&n\rightarrow\infty, T \text{ fixed} \Rightarrow \frac{T}{n}=0.
\end{aligned} \tag{2}
$$

In order to eliminate the unobserved fixed effect, α_i, first time differences can be taken, so that Eq. (1) becomes:

$$
\begin{aligned}
\Delta y_{i,t} =&\gamma\Delta y_{i,t-1}\mathcal{B}\Delta X_{i,t}+\Delta\epsilon_{i,t}, \qquad i\\
&=1,2,...,n; \quad t=2,3,...,T.
\end{aligned} \tag{3}
$$

This, however, creates a problem if the model is estimated through OLS since the first difference of the lagged dependent variable $\Delta y_{i,t-1}=y_{i,t-1}-y_{i,t-2}$ and the first difference of the idiosyncratic remainder component $\Delta\epsilon_{i,t}=\epsilon_{i,t}-\epsilon_{i,t-1}$ are not orthogonal. To obviate this problem, Holtz-Eakin et al. [15] proposed the following linear moment conditions:

$$
E(y_{i,s}\cdot\epsilon_{i,t})=0, \qquad t=3,4,...,T, \quad s=1,...,t-2. \tag{4}
$$

From (4), similar linear moment conditions can be derived for the covariates, depending on their degree of exogeneity[2]:

$$
\begin{aligned}
&E(x_{i,s}\cdot\epsilon_{i,t})=0, \quad t=3,4,...,T, \quad \text{with}\\
&s=1,...,t-2, \quad \text{if x is endogenous,}\\
&s=1,...,t-1, \quad \text{if x is predetermined,}\\
&s=1,...,T, \quad \text{if x is exogenous.}
\end{aligned}
$$

Summarizing in a less technical way, both the difference and system GMM methods share the idea with the standard panel fixed effect model of differencing the covariates and the dependent variable in order to get rid of the individual-specific unobserved fixed effects. However, given the presence among the covariates of the lagged dependent variable and of potentially endogenous regressors, they instrument all variables with their lags, whose number is determined by their degree of exogeneity.

In the difference GMM model, time differences are instrumented with levels. The system GMM model add a set of equations where levels of the regressors are instrumented by their time differences. This improves efficiency by adding more instruments, but rests on the assumption that the time differences of regressors are uncorrelated with the idiosyncratic fixed effects [26]. In the present case, this may be a very strong assumption, since it would entail, for example, that only the level of GDP is affected by countries unobserved fixed effects and not GDP growth. Therefore, all regressions except (9) and (10) have been run with both difference and system GMM and results are shown for comparison. In general, significance levels are far lower with difference GMM than with system GMM, thus the coefficients that are significant in the latter but not in the former should be taken with caution since they may be biased by the effect of idiosyncratic unobserved characteristics.

All regressions have been estimated with the Stata package *xtabond2* [26], using the two-step option, in which the residuals of the first step estimation are used to compute the weighting matrix necessary to the GMM estimator. All the reported *p*-values, in Tables 2, 3 and 4, have been obtained using Windmeijer [35] standard errors. Differently from Eq. (3), that uses first differences for eliminating fixed effects, all estimated regressions used forward orthogonal deviations, where the average of all future available observations of a variable is subtracted to its level at time *t* instead of the value of the previous time period [26]. This improves efficiency in unbalanced datasets with several missing values, as the present case, by allowing to discard less observations.

Recalling the previous discussion about the degree of endogeneity of regressors, in all regressions the number of floods and droughts and the time periods dummies have been assumed to be strictly exogenous, whereas all other covariates are treated as endogenous. All available lags have been used as instruments given the reduced number of time periods, and the "collapse" option has been selected to avoid the common problem of an excessive number of instruments. For the regressions from (1) to (8), Table 5, in the Appendix, reports the coefficients of the time periods, some basic statistics such as the number of observations and some diagnostic tests. For regressions (9) and (10), the same information is reported in Table 4, except the coefficients of the time periods that have been omitted. The diagnostic section consists in the Arellano-Bond test of first and second order autocorrelation where the null hypothesis is the absence of autocorrelation. Since the test is conducted on the first-differenced idiosyncratic errors, the AR(1) null hypothesis should be rejected. In fact, if the error term in levels is serially uncorrelated, this implies that the error term in first differences has negative first-order serial correlation. Furthermore, there should not be second-order serial correlation, thus the null of AR(2) should not be rejected. All presented models, from (1) to (10), respect this condition as visible from Tables 5 and 4. The other reported *p*-values refer to the Hansen test of over-identifying restrictions, whose null hypothesis is that the over-identifying restrictions are valid. Thus, the null hypothesis should not be rejected for the instruments to be valid and

[2] The previous and the following conditions must be modified accordingly if other lags of the dependent variable are present.

Table 2 Dynamic panel model regressions results

Dependent variable: child stunting (%)				
	Contemporaneous effect		**Lagged effect**	
	System GMM	**Diff. GMM**	**System GMM**	**Diff. GMM**
	(1)	**(2)**	**(3)**	**(4)**
Child_stunt_L1	1.000916***	0.981492***	0.9358482***	0.925766***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GDP_pc_PPP	0.0003147***	0.000190**	0.0002571*	0.000124
	(0.0000)	(0.0410)	(0.0670)	(0.2790)
GDP_pc_PPP2	−4.16E−09***	−1.24E−09	−3.63E−09	−2.45E−10
	(0.0040)	(0.4080)	(0.1500)	(0.8760)
Pop_tot	1.30E−06	−0.000010**	3.97E−06*	−7.38E−06
	(0.2860)	(0.0210)	(0.0980)	(0.3340)
Agr_area_pc	−0.098684***	−0.066930	−0.134570**	0.051216
	(0.0010)	(0.5390)	(0.0150)	(0.6950)
Irr_equip_perc	−0.014149	0.064167	−0.050317	−0.059216
	(0.6650)	(0.1100)	(0.2860)	(0.6310)
Manure_N_ph	−0.001579	-0.025398	0.021061	0.004803
	(0.8710)	(0.3260)	(0.2220)	(0.8280)
NPK_ph	−0.018327**	−0.008643*	−0.029240*	−0.010324
	(0.0270)	(0.0820)	(0.0690)	(0.2350)
Pest_ph	0.060168	0.008992	0.032874	0.006006
	(0.2200)	(0.7790)	(0.5510)	(0.8920)
Conflict_deaths	0.001866	0.024652	−0.004190	0.021051
	(0.9570)	(0.3770)	(0.9450)	(0.7830)
N_droughts	−0.088212	−0.131119	−0.024985	−0.000881
	(0.8420)	(0.7220)	(0.9610)	(0.9980)
N_floods	0.133482**	0.092947**	0.198906*	0.059366*
	(0.0240)	(0.0110)	(0.1000)	(0.0980)
CONST.	−3.29375***		−1.025374	
	(0.005)		(0.4610)	

Significance levels: *** = 1%, ** = 5%, * = 10%. *P*-values in brackets

this holds for all presented models except for model (3), where the null is rejected at the 10% level of significance.

Results and discussion

Table 2 shows the coefficient estimates of four models, all having the same regressors but, in the first two models, (1) and (2), they are contemporaneous, while in (3) and (4) they are in first lag. As mentioned, the coefficients of year dummies are reported in Table 5 in the Appendix. Models (1) and (3) are system GMM while (2) and (4) are difference GMM. In model (1), all coefficients related to agricultural inputs, namely agricultural land per-capita,

Table 3 Regressions results: additional economic controls and squared terms

Dependent variable: child stunting (%)				
	Economic controls		**Squared terms**	
	System GMM	**Diff. GMM**	**System GMM**	**Diff. GMM**
	(5)	(6)	(7)	(8)
Child_stunt_L1	1.0436***	0.9326426***	1.023739***	1.013486***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GDP_pc_PPP	0.000324***	0.000101	0.000296***	0.000201*
	(0.0010)	(0.3880)	(0.0000)	(0.0510)
GDP_pc_PPP2	−4.55E−09***	1.11E−09	−3.97E−09***	−1.72E−09
	(0.0040)	(0.5550)	(0.0010)	(0.3190)
Pop_tot	0.000001	−1.16E−05**	1.88E−06	−1.09E−05**
	(0.4350)	(0.0130)	(0.2170)	(0.0240)
Agr_area_pc	−0.128033***	−0.036745	−0.073970***	−0.135994
	(0.0010)	(0.7340)	(0.0010)	(0.1860)
Irr_equip_perc	−0.042709	0.084230	−0.036491	0.078485
	(0.2130)	(0.2390)	(0.3490)	(0.1260)
Manure_N_ph	−0.031924	−0.053416*	0.009997	−0.012279
	(0.1130)	(0.1000)	(0.7570)	(0.8840)
Manure_N_ph2			−0.000110	−5.54E−05
			(0.5490)	(0.8890)
NPK_ph	−0.012034***	−0.015545*	−0.015720	0.005395
	(0.0060)	(0.0660)	(0.1830)	(0.6210)
NPK_ph2			−0.000022	−2.90E−05
			(0.6620)	(0.3420)
Pest_ph	0.233708***	0.057025	0.366201**	0.082684
	(0.0040)	(0.4810)	(0.0160)	(0.2970)
Pest_ph2			−0.007394**	−0.001835
			(0.0230)	(0.1830)
Conflict_deaths	0.056200***	0.038172	0.023426	0.007498
	(0.0080)	(0.1200)	(0.4640)	(0.7590)
N_droughts	−0.814289	−0.383438	−0.588088	−0.341604
	(0.1210)	(0.2900)	(0.1700)	(0.3690)
N_floods	0.106631*	0.058062	0.121342*	0.082221*
	(0.0950)	(0.1880)	(0.0390)	(0.0570)
FDI	2.92E−08	4.67E−07		
	(0.9440)	(0.3220)		
Gross_cap_f	4.53E−08	−1.75E−07		
	(0.7600)	(0.3480)		
Inf_rate	0.000624	−0.017243		
	(0.8430)	(0.5360)		
Const.	−3.913445***		−3.838470***	
	(0.0080)		(0.0010)	

Significance levels: *** = 1%, ** = 5%, * = 10%. *P*-values in brackets

Table 4 Regressions results: agricultural productivity and low inputs dummy interacted with per-hectare NPK

Dependent variable: child stunting—system GMM (%)					
	Agricultural productivity	**Low inputs dummy**	**Ancillary infos**		
	(9)	**(10)**		**(9)**	**(10)**
Child_stunt_L1	0.936592***	0.996297***	*N. Instr.*	74	84
	(0.0000)	(0.0000)	*N. Obs.*	490	584
GDP_pc_PPP	0.000282**	0.000294***	*N. Countries*	83	85
	(0.0180)	(0.0010)			
GDP_pc_PPP2	−3.33E-09	−3.86E-09***	*AB Test AR(1)*	0.000	0.001
	(0.1060)	(0.0050)	*AB Test AR(2)*	0.782	0.744
Pop_tot	2.92E-06	1.31E-06	*Hansen Test*	0.220	0.268
	(0.1540)	(0.2450)			
Agr_area_pc	−0.103575***	−0.100090***			
	(0.0040)	(0.0010)			
Irr_equip_perc	−0.043159	−0.011304			
	(0.3110)	(0.7210)			
Manure_N_ph	0.003862	0.000472			
	(0.8110)	(0.9630)			
Pest_ph	0.063919	0.051774			
	(0.3390)	(0.3660)			
NPK_ph	−0.025255*	−0.018837**			
	(0.0940)	(0.0140)			
*Low_inp*NPK_ph*		−0.005828			
		(0.7300)			
Agr_prod	−0.002506**				
	(0.0110)				
Conflict_deaths	−0.007578	0.000311			
	(0.8670)	(0.9930)			
N_droughts	−0.121436	−0.153940			
	(0.7580)	(0.7370)			
N_floods	0.222404**	0.133371**			
	(0.0220)	(0.0360)			
Const.	−0.4614075				
	(0.7280)				

Significance levels: *** = 1%, ** = 5%, * = 10%. *P*-values in brackets

irrigation, organic fertilizers (manure), inorganic fertilizers and pesticides, have negative coefficients, except for the latter. However, only per-capita agricultural land (*Agr_area_pc*) and inorganic fertilizers (*NPK_ph*) are statistically significant, the former at 1% level and the latter at 5%. The coefficient of the lagged dependent variable is significant in all models at the 1% level. Furthermore, it is positive and close to one, implying a high persistency of child stunting.

Among the other regressors, only the number of floods—it is significant in all models except for (6)—and per-capita GDP are significant (at 5% level the former and at 1% the latter, both for its level and its squared form). The number of floods has a positive coefficient, implying that floods contribute to increase child stunting, as expected. Less straightforward is the role of per-capita GDP, since, theoretically, it is expected to decrease child stunting with declining efficacy. The positive coefficient of the level, and the negative of the squared term, imply an opposite scenario. Per-capita GDP is detrimental till a certain level and then it contributes to reduce child stunting at an increasing rate.

Model (2), relying on less stringent assumptions, provides similar results. The main difference is the loss of significance of per-capita agricultural land in favour of total population (*Pop_tot*), now significant at the 5% level and with a negative coefficient. Furthermore, the square of per-capita GDP loses significance as well.

In models (3) and (4), all regressors are present in first lag. In general, the significance of coefficients is reduced compared to their counterparts at time *t*. This effect is stronger for difference GMM, where only the lagged dependent and the number of floods are significant, with this last at the 10% level. This suggests that regressors have a stronger immediate rather than delayed impact. Regressions with both contemporaneous and lagged effects have been tested as well, but their results were similar to model (4), with almost all coefficients being not statistically significant. For these reasons, in the remaining models regressors are always present solely at time *t*.

Table 2 shows the results of models with additional economic controls, models (5) and (6), and with the squared terms of agricultural inputs, models (7) and (8). The addition of squared terms has the purpose of individuating eventual non-linearities, such as a declining rate in reducing child stunting. As in the previous table, odd numbers refer to models estimated with system GMM and even ones with difference GMM. As additional economic controls, per-capita foreign direct investments (*FDI*), per-capita gross capital formation (*Gross_cap_f*) and inflation rate (*Inf_rate*) are added to the covariates seen in Table 2. None of them are statistically significant in both GMM methods, but some other regressors are affected by their introduction by changing their significance level. Model (5) differs compared to model (1) insofar the coefficients of pesticides and conflicts gain significance, both at 1% level. Both of them are positive and if this is the expected result for conflicts, it is less so for pesticides. This may be due to the fact that pesticides are a risk enhancing input, improving yields but increasing the variability of income. However, by looking at model (7), where the squared term of pesticides is added, it can be observed that coefficients have the same sign as per-capita GDP, positive for the level and negative for the squared term (both significant at 5% level). Thus, pesticides may also contribute to decrease child stunting after a certain threshold at an increasing rate.

When difference GMM is adopted—model (6)—pesticides and conflicts lose significance, but the coefficient of manure results significant at the 10% level. Its sign is negative, as expected, and its magnitude is more than threefold that of inorganic fertilizers. A possible reason is that manure is a source of soil organic carbon (SOC), an important determinant of the ability of plants to absorb nutrients, whereas inorganic fertilizers are not. As seen in model (2), and similarly to model (8), the shift from system to difference GMM causes per-capita agricultural land to lose significance in favour of total population, both having a negative coefficient.

When the squared terms of manure, inorganic fertilizers and pesticides are added, none of their coefficients, including the ones related to the levels, are significant except for pesticides in (7), as already discussed. Also inorganic fertilizers, whose coefficient is significant in all other models except in (4), does not reach the 10% threshold. This may be due to a problem of collinearity or to an excessive number of regressors. In model (8), in particular, almost all coefficients are not significant.

The last two models, (9) and (10), are both system GMM, with the former having the addition of agricultural production (*Agr_prod*), as per-capita value, among the regressors, while the latter the interaction between inorganic fertilizers and a dummy (*Low_inp*) individuating countries with a low level of inorganic fertilizers use: the dummy takes the value of one if less than 25 kg per hectare of combined N, P and K from inorganic fertilizers are used on agricultural land in one year, with 25 kg/ha being the median value of *NPK_ph*. The coefficient of the value of agricultural productivity should capture the effect on child stunting of improved agricultural production originating from means other than inputs intensification: e.g. advances in agronomic knowledge or mechanization. As expected, its coefficient is negative and significant (5% level), implying that improving productivity is beneficial in reducing child stunting. This also means that, beyond inputs intensification, there have been significant gains in productivity in the sampled years originating from other sources. It has to be noted, however, that its coefficient loses significance if the model is estimated using difference GMM. The signs and the significance levels of the other coefficients are fully consistent with model (1) except for the loss of significance of the square of per-capita GDP.

If models (7) and (8) had the addition of squared terms for capturing eventual non-linearities in the effect of agricultural inputs, among which inorganic fertilizers, model (10) tries to asses if the per-hectare level of combined N, P, and K has a greater impact in reducing child stunting for lower starting values. The negative sign of its coefficient would then imply that additional units of inorganic fertilizers are more beneficial for countries with low levels of fertilization. This sounds reasonable, but the coefficient is not significant and this holds if difference GMM is adopted instead. Once more, the signs and the significance of the other coefficients are very similar to model (1).

Policy implications

The present analysis has shown a mild impact of agricultural inputs in reducing child stunting. Despite generally having the expected negative sign, only few of their coefficients are statistically significant. The coefficient of the combined macro-nutrients from inorganic fertilizers is the main exception, being significant in most of the estimated models at least at the 10% level. Its average magnitude ranges between − 0.015 and − 0.02, implying that an increase in combined N, P and K of 10 kg per hectare of agricultural land would likely decrease child stunting of 0.15–0.2 percentage points. This seems a mild value since it would take additional 50 kg of N, P and K from inorganic fertilizers to have a reduction of 1 percentage point in child stunting. However, considering that the median value of *NPK_ph* is 25 kg and the recommended quantity of combined N, P and K for several cereals is well above 200 kg, an intensification in the use of this input may bring significant benefits in reducing child stunting. Furthermore, such a low median value implies that, for several countries, an intensification of N–P–K use would have a low impact on the environment. This seems to be particularly true for African countries. Note that, additional regressions, whose results are not reported, have been made splitting *NPK_ph* into its three components. Despite all their coefficients being negative, none of them were statistically significant.

The other input with a coefficient often significant is per-capita agricultural land, although significance is achieved only under system GMM, leaving the doubt that idiosyncratic fixed effects may bias this result. Since agricultural land is mostly fixed, the policy options are reduced. Favouring land concentration may be a possibility, but only insofar labour options are available for farmers exiting from the agricultural sector. This would then call for a balanced growth and for increasing the level of industrialization and of the third sector. Agricultural production, or else, improvement in agricultural productivity not derived from inputs intensification, is another regressor significant only when system GMM is adopted, therefore the same caveats as for *Agr_area_pc* apply. Mechanization and advances in knowledge are likely elements represented by this variable, therefore they should be fostered for reducing malnutrition.

The coefficients of the other agricultural inputs are almost always not significant. Manure is significant only in one model, the difference GMM with additional economic controls. Its magnitude, however, is far higher than inorganic fertilizers, thus it is possibly even more beneficial for reducing child stunting. Pesticides are significant only in two models, with the level having a puzzling positive coefficient. When its squared term is introduced, however, this has a negative coefficient, with a behaviour similar to per-capita GDP. Finally, it is surprising the lack of significance of irrigation in all models, implying this input is inconsequential in reducing child stunting. Several reasons may contribute to explain this fact. First of all, irrigation is proxied by the area equipped for it, rather than by the actual irrigated area. Thus, it is a less precise proxy[3]. Its inter-temporal variability may also be lower, further contributing to reduce significance. Finally, the average value for low-income countries is a mere 5% of agricultural land equipped for irrigation, with a median value as low as 0.8%. With such low values, it may not be able to impact child stunting.

Conclusions

In conclusion, the present study tries to shed light on the crucial relationship between agricultural inputs and nutritional outcomes, addressing a significant gap in the existing literature. By using a comprehensive country-level analysis spanning two decades, inorganic fertilizers have been identified as the most significant input in reducing child stunting, chosen as a proxy for undernourishment. Per-capita agricultural land is the second input in terms of statistical significance, reaching it in all models estimated through system GMM. Manure, pesticides and irrigation are never or almost never significant.

Clearly, the most immediate message seems to be the intensification of inorganic fertilizers use, particularly in countries with very low levels of current adoption. In such countries, in fact, there might be larger gains and the environmental impact should be minimal. Mechanization, knowledge and land concentration are likely to be other factors helpful in reducing child stunting.

The lack of significance of the other agricultural inputs must be taken with caution rather than being interpreted as evidence of inconsequentiality. Irrigation, in particular, has been proxied by a somehow weak variable due to lack of data in better alternatives. The choice of the dependent variable may be an additional reason, since child stunting is a narrow subset of undernourishment and may be caused by additional factors other than alimentation alone. It has been chosen as a proxy for undernourishment since this last is plagued by several imputed data, leading to possible bias. Since undernourishment is likely to be more directly impacted by agricultural production, the examined inputs may gain significance. This calls for better data regarding undernourishment in order to gain a broader picture compared to the one offered by this paper.

Appendix

See Fig. 2, Table 5.

[3] Adopting the variable of actually irrigated land would have caused the elimination of several countries, particularly African, from the analysis for lack of information.

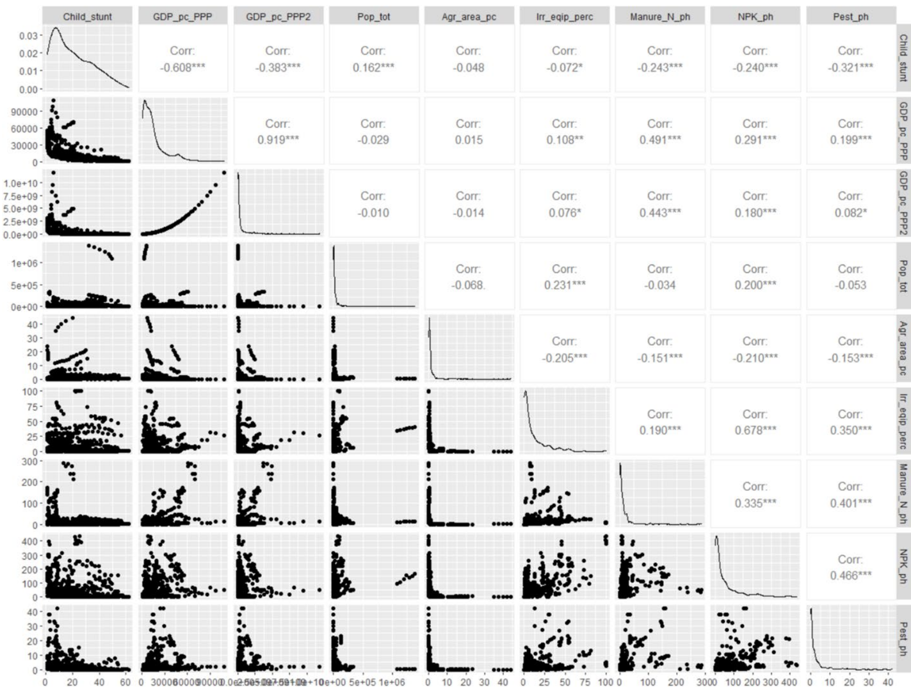

Fig. 2 Correlation matrices of selected variables

Table 5 Ancillary information for regressions in Tables 2 and 3

Years dummies	(1)	(2)	(3)	(4)
00–02	–	–	–	–
03–05	0.255773	0.174720	0.319497**	0.531647
06–08	−0.163919	−0.171393	0.247306	0.186002
09–11	−0.353740**	−0.319637	0.200180	−0.112768
12–14	−0.265673**	−0.256717	0.156664	−0.147238
15–17	−0.104318	−0.087286	0.092647	−0.035457
18–20	–	–	–	–
Reg. statistics				
N. Instr.	77	66	68	57
N. Obs.	504	419	502	417
N. Countries	85	85	85	85
Diagnostic tests	*P*-values			
AB test AR(1)	0.001	0.001	0.001	0.001
AB test AR(2)	0.774	0.749	0.977	0.847
Hansen test	0.404	0.594	0.079	0.253
Years dummies	**(5)**	**(6)**	**(7)**	**(8)**
00–02	–	–	–	–
03–05	−0.130085	0.407457	0.069195	0.462385
06–08	−0.542102***	−0.013306	−0.388002**	0.378093
09–11	−0.611744***	−0.234650	−0.530272***	0.293964
12–14	−0.467398*	−0.231598	−0.418716***	0.190552*
15–17	−0.190846***	−0.112314	−0.149870*	0.104607
18–20	–	–	–	–
Reg. statistics				
N. Instr.	98	84	98	84
N. Obs.	468	387	504	419
N. Countries	81	80	85	85
Diagnostic tests	*P–values*			
AB test AR(1)	0.004	0.006	0.008	0.002
AB test AR(2)	0.763	0.442	0.945	0.800
Hansen test	0.832	0.498	0.590	0.633

Significance levels: *** = 1%, ** = 5%, * = 10%

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Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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References

1. Abay KA, Ibrahim H, Breisinger C. Food policies and obesity in low-and middle-income countries. World Dev. 2022;151. https://doi.org/10.1016/j.worlddev.2021.105775.

2. Abu-Fatima O, Abbas AAG, Racalbuto V, Smith L, Pizzol D. Child undernutrition in Sudan: the social and economic impact and future perspectives. Am J Trop Med Hyg. 2021;104(3):1149. https://doi.org/10.4269/ajtmh.20-1251.
3. Arellano M, Bond S. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev Econ Stud. 1991;58(2):277–97. https://doi.org/10.2307/2297968.
4. Arellano M, Bover O. Another look at the instrumental variable estimation of error-components models. J Econ. 1995;68(1):29–51. https://doi.org/10.1016/0304-4076(94)01642-D.
5. Behrman JR, Wolfe BL. More evidence on nutrition demand: income seems overrated and women's schooling underemphasized. J Dev Econ. 1984;14(1):105–28. https://doi.org/10.1016/0304-3878(84)90045-2.
6. Berti PR, Krasevec J, FitzGerald S. A review of the effectiveness of agriculture interventions in improving nutrition outcomes. Public Health Nutr. 2004;7(5):599–609. https://doi.org/10.1079/PHN2003595.
7. Blundell R, Bond S. Initial conditions and moment restrictions in dynamic panel data models. J Econ. 1998;87(1):115–43. https://doi.org/10.1016/S0304-4076(98)00009-8.
8. Christiaensen L, Demery L, Kuhl J. The (evolving) role of agriculture in poverty reduction—an empirical perspective. J Dev Econ. 2011;96(2):239–54. https://doi.org/10.1016/j.jdeveco.2010.10.006.
9. Craig P. Obesity and culture. Clinical Obesity in Adults and Children, 2009:41–57.
10. De Janvry A, Sadoulet E. Agricultural growth and poverty reduction: additional evidence. World Bank Reserv Obs. 2010;25(1):1–20. https://doi.org/10.1093/wbro/lkp015.
11. Evenson RE, Gollin D. Assessing the impact of the Green Revolution, 1960 to 2000. Science. 2003;300(5620):758–62. https://doi.org/10.1126/science.1078710.
12. FAO, Ifad, UNICEF, WFP, and WHO. The state of food security and nutrition in the world. Urbanization, agrifood systems transformation and healthy diets across the rural-urban continuum. Technical report, Rome, FAO. 2023. https://doi.org/10.4060/cc3017en.
13. Fritsch M, Andrew AYP, Schnurbus J. pdynmc: A package for estimating linear dynamic panel data models based on nonlinear moment conditions. R J. 2021;13(1):218.
14. Fuglie KO. Is agricultural productivity slowing? Glob Food Sec. 2018;17:73–83. https://doi.org/10.1016/j.gfs.2018.05.001.
15. Holtz-Eakin D, Newey W, Rosen HS. Estimating vector autoregressions with panel data. Econometrica: Journal of the econometric society, 1988;1371–1395. https://doi.org/10.2307/1913103.
16. IPCC. Climate Change 2014: synthesis report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report, Geneva, IPCC. 2014. https://doi.org/10.59327/IPCC/AR6-9789291691647.
17. IPCC. Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report, Geneva, IPCC. 2022. https://doi.org/10.59327/IPCC/AR6-9789291691647.
18. Jones CA, Sands RD. Impact of agricultural productivity gains on greenhouse gas emissions: a global analysis. Am J Agric Econ. 2013;95(5):1309–16.
19. Laborde D, Mamun A, Martin W, Piñeiro V, Vos R. Agricultural subsidies and global greenhouse gas emissions. Nat Commun. 2021;12(1):2601. https://doi.org/10.1038/s41467-021-22703-1.
20. Marson M, Saccone D, Vallino E. Total trade, cereals trade and undernourishment: new empirical evidence for developing countries. Rev World Econ. 2023;159(2):299–332. https://doi.org/10.1007/s10290-022-00468-z.
21. Mary S. Hungry for free trade? Food trade and extreme hunger in developing countries. Food Secur. 2019;11(2):461–477 https://doi.org/10.1007/s12571-019-00908-z.
22. Mary S, Stoler A. Does agricultural trade liberalization increase obesity in developing countries? Rev Dev Econ. 2021;25(3):1326–50. https://doi.org/10.1111/rode.12757.
23. McArthur JW, McCord GC. Fertilizing growth: agricultural inputs and their effects in economic development. J Dev Econ. 2017;127:133–52. https://doi.org/10.1016/j.jdeveco.2017.02.007.
24. Menegat S, Ledo A, Tirado R. Greenhouse gas emissions from global production and use of nitrogen synthetic fertilisers in agriculture. Sci Rep. 2022;12(1):14490. https://doi.org/10.1016/j.envint.2019.105366.
25. Mughal M, Fontan Sers C. Cereal production, undernourishment, and food insecurity in South Asia. Rev Dev Econ. 2020;24(2):524–45. https://doi.org/10.1111/rode.12659.
26. Roodman D. How to do xtabond2: an introduction to difference and system GMM in Stata. Stand Genomic Sci. 2009;9(1):86–136. https://doi.org/10.1177/1536867X0900900106.
27. Salois MJ, Tiffin R, Balcombe KG. Impact of income on nutrient intakes: implications for undernourishment and obesity. J Dev Stud. 2012;48(12):1716–1730 https://doi.org/10.1080/00220388.2012.658376.
28. Santeramo FG, Shabnam N. The income-elasticity of calories, macro- and micro-nutrients: what is the literature telling us? Food Res Int. 2015;76:932–7. https://doi.org/10.1016/j.foodres.2015.04.014.
29. Serrão JE, Plata-Rueda A, Martínez LC, Zanuncio JC. Side-effects of pesticides on non-target insects in agriculture: a mini-review. Sci Nat. 2022;109(2):17. https://doi.org/10.1007/s00114-022-01788-8.
30. Shankar B, Poole N, Bird FA. Agricultural inputs and nutrition in South Asia. Food Policy. 2019;82:28–38. https://doi.org/10.1016/j.foodpol.2018.10.011.
31. Sobal J. Social and cultural influences on obesity. International Textbook of Obesity, 2001:305–322.
32. United-Nations. World population prospects 2022: summary of results. New York, United Nations: Technical report; 2022.
33. Walls HL, Johnston D, Tak M, Dixon J, Hanefeld J, Hull E, Smith RD. The impact of agricultural input subsidies on food and nutrition security: a systematic review. Food Secur. 2018;10:1425–36. https://doi.org/10.1007/s12571-018-0857-5.
34. WHO. Global nutrition targets 2025: stunting policy brief. Technical report: World Health Organization; 2014.
35. Windmeijer F. A finite sample correction for the variance of linear efficient two-step GMM estimators. J Econ. 2005;126(1):25–51. https://doi.org/10.1016/j.jeconom.2004.02.005.
36. Wołejko E, Jabłońska-Trypuć A, Wydro U, Butarewicz A, Łozowicka B. Soil biological activity as an indicator of soil pollution with pesticides—a review. Appl Soil Ecol. 2020;147. https://doi.org/10.1016/j.apsoil.2019.09.006.
37. Wolfe BL, Behrman JR. Is income overrated in determining adequate nutrition? Econ Dev Cult Change. 1983;31(3):525–49. https://doi.org/10.1086/451340.

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