INTERNATIONAL MONETARY FUND

How do Economic Growth and Food Inflation Affect Food Insecurity?

Christian Bogmans, Andrea Pescatori, Ervin Prifti

WP/24/188

2024
SEP

WORKING PAPER

 WP/24/188

IMF Working Paper

Research Department

How do Economic Growth and Food Inflation Affect Food Insecurity?

Prepared by Christian Bogmans, Andrea Pescatori, and Ervin Prifti

Authorized for distribution by Petya Koeva Brooks
August 2024

ABSTRACT: During the global recession of 2020 food insecurity increased substantially in many countries around the world. Fortunately, the surge in food insecurity quickly came to a halt as the world economy returned to its positive growth path, despite double-digit domestic food inflation in most countries. To shed light on the relative importance of income growth and food inflation in driving food insecurity, we employ a heterogeneous-agent model with income inequality, complemented by novel cross-country data for the period 2001-2021. We use external instruments (changes in commodity terms-of-trade, external economic growth, and harvest shocks) to isolate exogenous variation in domestic income growth and food inflation. Our findings suggest that income growth is the dominant driver of annual variations in food insecurity, while food price inflation plays a somewhat smaller role, aligning with our model predictions.

RECOMMENDED CITATION: Bogmans, Christian, Pescatori, Andrea, Prifti, Ervin (2024). “How do Economic Growth and Food Inflation Affect Food Insecurity?”. IMF Working Paper WP/24/188. International Monetary Fund, Washington DC.

JEL Classification Numbers:	Q11, Q1, I38
Keywords:	Food insecurity; inclusive growth; food inflation; inequality; diet.
Author’s E-Mail Address:	cbogmans@imf.org;apescatori@imf.org;eprifti@imf.org

WORKING PAPERS

How do Economic Growth and Food Inflation Affect Food Insecurity?

Prepared by Christian Bogmans, Andrea Pescatori, and Ervin Prifti[1]

[1] The authors would like to thank Petya Koeva Brooks, Gita Gopinath, Ishan Nath, and Tim Willems for their valuable suggestions, and Claire Li, Wenchuan Dong, and Joseph Moussa for their excellent research assistance. We have benefited from many discussions with and suggestions from participants of the IMF surveillance meeting, the April 2023 IMF Analytical Corner presentation, and the IMF Research Department Lightning Seminar. A very preliminary version of our paper was presented at the 2021 British Society for Population Studies Annual Conference at the London School of Economics. The data underlying this article will be shared on reasonable request to the corresponding author. The authors declare that they did not receive external funding for this research and that there are no conflicts of interest.

1 Introduction

Between 2019 and 2021 the number of undernourished people increased by approximately 126 million worldwide, prompting the heads of a group of international organizations including the Food and Agriculture Organization and the International Monetary Fund to declare the onset of a new global food security crisis (FAO et al., 2022).[1] The increase in the prevalence of undernourishment (PoU), a food security indicator that measures the share of the population whose dietary energy intake is below a minimum caloric threshold, was especially sharp during the pandemic-induced global recession of 2020. That year saw global real GDP contract by 2.9 percent, the steepest decline since the Great Depression. When the worst of the 2020 recession was over, however, food inflation then surged on account of supply chain disruptions and Russia's invasion of Ukraine. Despite a global average increase of 19 percent in domestic food prices during 2021 and 2022, the global PoU stabilized in 2022. This coincided with a cumulative 10 percent increase in real world GDP over the same period. Notwithstanding cross-country differences in food inflation and recovery in economic activity, these events suggest that in recent years income fluctuations exerted a bigger impact on food insecurity than food inflation.[2] [3]

Against this background, this paper sets out to quantify the impact of fluctuations in real income growth and food inflation on food insecurity, as measured by the PoU and two measures of diet composition (e.g., grams of animal protein per capita per day). To this end we utilize both a novel theoretical model and panel data with instrumental variables. Our main finding is that the positive effects of income growth in reducing the PoU are somewhat stronger than the negative effects posed by food inflation. As we highlight in the paper's conclusion, we believe these findings are of interest for policymakers seeking to tackle food insecurity in the most efficient and effective manner.

To help organize our thinking regarding the macroeconomic determinants of food in-

[1]Previous food crises with a global scope include 1973, 2008-2009, and 2010-2012.

[2]By the time of finalizing our empirical analysis in 2023, 2021 was the last year for which data on the prevalence of undernourishment was available. While we are partially motivated also by events in 2022 and 2023 that are not in our dataset, cross-country variation in food inflation, economic growth and food insecurity fluctuations between 2001-2021 is used to conduct a horse race between food inflation and economic growth in driving PoU fluctuations.

[3]Similarly, the global PoU declined between 2008 and 2013, albeit at a markedly slower pace than during the 2002-2007 period, despite the 2008-2009 and 2010-2012 episodes of high food commodity prices.

security, we present a stylized heterogeneous-agent model. Households posses isoelastic non-homothetic CES preferences à la Matsuyama (2019) over food and non-food, and vary in terms of their level of income. Food insecurity is defined as the fraction of households (at the lower end of the income distribution) who fall below an exogenous threshold in terms of food consumption. Poverty, on the other hand, occurs when household real income falls below a certain minimum. We also differentiate between an urban and rural economy variant of our model. In the rural variant, an increase in food prices leads to a windfall gain for farmers, directly increasing household income. Calibrating our model to the data for different regions in the world, the model delivers testable qualitative and quantitative predictions about the semi-elasticities of food insecurity with respect to income per capita, food prices, and inequality.

The model is simple enough to show in a transparent way that the responsiveness of food insecurity to food price changes, for example, hinges on three critical factors: (i) the shape of the income distribution, (ii) the magnitude of the substitution elasticity relative to the income elasticity of food demand, and (iii) the degree of income redistribution. At the same time, the model is just complex enough to generate some unexpected predictions. For instance, it suggests that in rural areas higher food prices might have divergent and even opposite impacts on food insecurity and poverty respectively. Specifically, our calibrated model shows that while higher food prices increase food insecurity, albeit modestly, in rural settings—a finding that aligns with our empirical evidence as well as the existing literature—they may simultaneously reduce poverty, a result also supported by the literature.

Turning to the quantitative predictions, the calibrated model puts the global average income semi-elasticity of the PoU at approximately -0.12 percentage points (pp). Stated differently, a doubling of income per capita should lead to a sizeable potential reduction of the PoU by 12 pp. Regarding the effect of food prices on the PoU, our model predicts that the semi-elasticity will be positive yet close to 0 in rural areas and around 0.12 pp in urban areas. Thus, when analyzing country-level PoU data, we would expect to find the food price elasticity to lie within these two bounds.

To empirically test the predictions of our model, we use a novel longitudinal dataset covering 142 countries for a period of two decades (2001-2021). We construct and collect from the literature several instrumental variables, namely (i) changes in a country's commodity terms-of-trade, (ii) economic growth in trading partners, and (iii) external cereal harvest shocks, to isolate exogenous variation in domestic income growth and food inflation so that we can estimate their causal impact on food insecurity.

Our main findings are as follows. A 1 percentage point increase in economic growth leads to an approximately 0.11 pp reduction in the share of undernourished (0.79%), close to the prediction of our calibrated model.[4] In line with our model's qualitative predictions, food inflation plays a more modest role, compared to real GDP growth, as the corresponding undernourishment elasticity, estimated at -0.06 pp (0.46%), is about 40% smaller. Empirical results also reveal that the semi-elasticity of undernourishment to income shows a slight tendency to decrease as inequality grows. Finally, although countries that start out with higher levels of undernourishment show higher rates of reduction, the pace is slow, providing modest evidence of cross-country convergence in undernourishment.

Contributions and Literature. Most research on food insecurity focuses on its sociodemographic determinants at the micro level (Borjas, 2004; Gundersen et al., 2011). Our study contributes to a handful of papers that analyze the effects of aggregate economic factors on food insecurity (Headey, 2013; Gregory and Coleman-Jensen, 2013).

The paper makes two contributions to the literature on food insecurity and inclusive growth more generally. First, to the best of our knowledge we are the first to present a tractable heterogeneous agent model of the macro drivers of food insecurity that generates testable predictions. Second, we simultaneously estimate the effects of income growth and food inflation on changes in food insecurity, allowing us to rank them in terms of quantitative importance, using an empirical strategy that explicitly addresses endogeneity concerns.[5] This is relevant because there is potential for reverse causality even in the short run, as can be the case when governments react to a deterioration in food security by increasing social protection spending or influencing food prices through monetary policy or direct control, which in turn may affect next year's growth. Ignoring these issues leads to estimates biased towards zero, especially for the income elasticity of undernourishment.

[4]A supplementary appendix contains results showing that income changes also alter diets, as households react to recessions by replacing expensive calories sources (e.g. proteins) with cheaper ones (e.g. carbs).

[5]Previous studies have only examined the relationship between food insecurity and individual macroeconomic variables in isolation. A notable exception, albeit on a different yet related topic, is a recent study by Mahler et al. (2021), who find that to predict national poverty rates a simple approach based on real GDP per capita growth performs nearly as well as models using statistical learning on 1000+ variables.

The cross-country studies from Headey (2013), Soriano and Garrido (2016), and Headey and Hirvonen (2023) are closest to our thematic focus. Soriano and Garrido (2016) find a 0.29% reduction in the share of food insecure for every 1 pp increase in real GDP per capita growth, in line with our OLS estimates but almost three times smaller than our preferred IV approach, which corrects for possible endogeneity and is also much closer to the magnitudes predicted by our theoretical model.[6] Headey (2013) finds that higher food prices exacerbate food insecurity. His measure of food insecurity is a subjective micro-level one, however, which makes his estimates not directly comparable to ours, since we use objective aggregate indicators of food insecurity. The latter are non perception-based and may offer more scope for cross-country comparability. Headey and Hirvonen (2023) show that increases in annual real food prices predict reductions in poverty, but not in non-agrarian or more urban countries. By distinguishing between rural and urban settings and using nonhomothetic preferences, our model can explain why higher food prices lower poverty but increase food insecurity, which is consistent with these before-mentioned studies. Evidence for the farmer-income mechanism of higher food prices is presented by Dhingra and Tenreyro (2021).

There are several secondary contributions to the literature worth noting. First, we study both quantitative and qualitative aspects of food insecurity to capture the connection between quantitative sufficiency and qualitative adequacy of diets.[7] The branch of the literature dealing with the latter has been dominated by micro studies looking into dietary changes in response to economic shocks (D'Souza and Jolliffe, 2014). Second, we are also the first to consider the role of social protection as a fiscal policy instrument to tackle food insecurity, while previous research had focused on how access to specific social protection programs (e.g., cash/food transfers) affects household food insecurity (Tiwari et al., 2016).

[6]In a previous working paper, we also analyzed the role of economic growth and food inflation in driving PoU using comparable panel data and regression analysis (see Bogmans et al. (2021)). That paper lacked a model to explain potential discrepancies between growth and food inflation as drivers of PoU. Another improvement of the current paper is the use of external instruments to address endogeneity concerns.

[7]Due to space considerations, results for qualitative measures of food insecurity are delegated to a supplementary online appendix.

2 Model

2.1 Model Ingredients

Three manifestations of food insecurity with increasing degrees of severity are: worry about food, inadequate diet quality, and insufficient calorie intake (Wilde, 2011). Economists have focused on the latter manifestations, which can be measured through objective indicators while the former is subjective as it depends on perceptions. When an individual is below the minimum calorie intake there is a severe disutility from the physical and psychological discomfort of hunger. The marginal utility of extra calories is therefore high for calorie-deprived individuals, leading them to acquire the cheapest available source of calories, typically cereals, roots and tubers. Once more favorable combinations of income and food prices lift individuals above subsistence calorie levels, the marginal utility of extra calories declines rapidly and they substitute away from staples, introducing better tasting and more expensive foods into their diets, like meat, fish and fruits.

Nonhomothetic Preferences for Food and Non-Food. For the third and most severe aspect of food insecurity we present a stylized partial equilibrium model of food insecurity. Households buy food and non-food to maximize utility from consumption. Those that fall below an exogenous food consumption level are classified food insecure. Since the model features only one type of food, we are abstracting from any diet composition channel that, in case of negative shocks, would slow down (but not reverse) households descent into food insecurity.[8] A mass one of households is indexed by h on the continuum $h \in [0, 1]$. Each household has identical affine non-homothetic preferences, U, over a food bundle, C_F, and a non-food bundle of consumption, C_{NF}, such that

$$U = \begin{cases} v(C_F) & \text{for } 0 < C_F < \underline{C_F} \\ u(C_F - \underline{C}_F, C_{NF}) & \text{for } C_F \geq \underline{C_F} \end{cases}$$

where $\underline{C}_F > 0$ is the food subsistence requirement, or basic need threshold, such that $\sup_{C_F} v(c_F) < \inf_{C_F, C_{NF}} u(C_F, C_{NF})$, with C_F and C_{NF} defined in their respective support intervals. This util-

[8]For more insights into the economics of diet choice and caloric constraints, we refer the interested reader to Lancaster (1966), Gilley and Karels (1991), and Jensen and Miller (2008).

ity function captures the notion that households have lexicographic preferences until food consumption reaches a basic need level.

We follow a number of recent papers in the literature on structural change, including Matsuyama (2019), Comin et al. (2021), and Nath (2023), by assuming that subsistence utility U is implicitly defined through the following nonhomothetic utility function:

$$\left(\alpha^{\frac{1}{\eta}} U^{\frac{\epsilon_F-\eta}{\eta}} (C_F - \underline{C_F})^{1-\frac{1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} U^{\frac{\epsilon_{NF}-\eta}{\eta}} C_{NF}^{1-\frac{1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \equiv 1 \quad \text{for} \quad C_F \geq \underline{C_F} \tag{1}$$

where $\eta \in (0,1) \cup (1,\infty)$ and $\epsilon_F > 0$ ($\epsilon_{NF} > 0$) are parameters representing the constant elasticity of substitution and the income elasticity of food (non-food) respectively, and where we have extended the isoelastic nonhomothetic CES function by including a food subsistence requirement. The latter adjustment has been made to ensure that under certain parameter restrictions (i.e. $\epsilon_{NF} = \epsilon_F = 1$) eq. (1) reduces to Stone-Geary CES, until recently the most popular choice for modeling nonhomothetic preferences.

Each household earns an income $y(h)$, with households ranked on the continuum in ascending order such that $y(h') > y(h'') \Leftrightarrow h' > h''$. Gross disposable income is $y^d(h) = y(h) + \tau(h)$ where $\tau : [0,1] \to \mathbb{R}$ is a redistributive tax scheme such that $\int_0^1 \tau(h)dh = 0$. Let μ_y denote average per capita income. Then social protection expenditures collected by (or taxes paid by) household h are determined as follows $\tau(h) = -\kappa(y(h) - \mu_y)$ such that

$$y^d(h) = (1-\kappa)y(h) + \kappa\mu_y. \tag{2}$$

The variable $\kappa \in [0,1]$ controls the degree of redistribution and determines minimum income as a fraction of per capita income, $\kappa\mu_y$. The size of the redistribution is thus proportional to κ and to income dispersion. If $\kappa = 0$ or $y(h) = \mu_y$ for all h then $y^d = y$.

Each household is a price taker in the food market. Let p_F and p_{NF} be the price of food and nonfood respectively. Then households maximize eq. (1) subject to the budget constraint, $p_F C_F + p_{NF} C_{NF} = y^d(h) - p_F \underline{C_F}$, resulting in the following demand for food and non-food respectively:

$$C_F(h) = \begin{cases} \frac{y^d(h)}{p_F} & \text{for } C_F < \underline{C_F} \\ \underline{C_F} + \underbrace{\alpha \left(\frac{y^d(h) - p_F \underline{C_F}}{P} \right)^{\epsilon_F - 1} \left(\frac{p_F}{P} \right)^{1-\eta}}_{\equiv m_F} \left(\frac{y^d(h) - p_F \underline{C_F}}{p_F} \right) & \text{for } C_F \geq \underline{C_F} \end{cases} \tag{3}$$

$$C_{NF}(h) = \begin{cases} 0 & \text{for } C_F < \underline{C_F} \\ \underbrace{(1-\alpha) \left(\frac{y^d(h) - p_F \underline{C_F}}{P} \right)^{\epsilon_{NF} - 1} \left(\frac{p_{NF}}{P} \right)^{1-\eta}}_{\equiv m_{NF}} \left(\frac{y^d(h) - p_F \underline{C_F}}{p_{NF}} \right) & \text{for } C_F \geq \underline{C_F} \end{cases} \tag{4}$$

where m_F and m_{NF} constitute the budget shares for food and non-food respectively, and where the price index $P = P(p_F, p_{NF}, y^d(h))$, satisfying $U = \frac{y^d(h) - p_F \underline{C_F}}{P}$, is implicitly given by

$$[m_F + m_{NF}]^{\frac{1}{1-\eta}} \equiv 1 \tag{5}$$

Defining Food Insecurity and Poverty. Next, let us define undernourishment and poverty, two concepts that in the literature are often used almost interchangeable. We will show that the food price elasticity of poverty and the food price elasticity of food insecurity are (quantitatively) different, and that it may thus be important to differentiate between the two.

First, a household is undernourished if its calorie intake falls below a certain minimum $\underline{Q}$, that is, $C_F \leq \underline{Q}$, where $\underline{Q}$ is potentially higher than the subsistence or basic need threshold, i.e., $\underline{C_F} = \lambda \underline{Q}$ with $\lambda \leq 1$. Second, a household is defined as poor when its level of real income (or welfare) falls below a minimum, $\frac{y^d(h) - p_F \underline{C_F}}{P} \equiv R \leq \underline{R}$.

Armed with these definitions and making use of eqs. (3) and (2), we can then derive the following expressions for the income levels that coincide with the undernourishment and poverty thresholds, that is,

$$y^{PoU} = \frac{\tilde{\alpha} p_F \underline{Q} - \kappa \mu_y}{1 - \kappa}, \tag{6}$$

and

$$y^{POV} = \frac{P\underline{R} + p_F \underline{C_F} - \kappa \mu_y}{1 - \kappa}, \tag{7}$$

where

$$\tilde{\alpha} \equiv \frac{\lambda \alpha^{\frac{1}{\epsilon_F}} + \left((1-\lambda) \underline{Q}^{1-\epsilon_F} \left(\frac{p_F}{P}\right)^{\eta-\epsilon_F} \right)^{\frac{1}{\epsilon_F}}}{\alpha^{\frac{1}{\epsilon_F}}} > 0. \tag{8}$$

Note that $1/\tilde{\alpha}$ is the share of nominal income that affords the household the minimum food basket $\underline{Q}$. The right-hand sides of eqs.(6)-(7) depend on y^{PoU} and y^{POV} (via P), and thus represent implicit solutions to y^{PoU} and y^{POV}. In the standard CES case ($\epsilon_{NF} = \epsilon_F = 1$), however, P no longer depends on income and thus (6)-(7) represent explicit solutions.

Closing the model: inequality in urban and rural economies. Let income per capita y be a continuous random variable with probability density function (PDF) $f(y;\boldsymbol{\theta})$, cumulative distribution function (CDF) $F(y;\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a set of (typically two of three) parameters. The mean and standard deviation of the distribution are denoted by μ_y and σ_y respectively. The CDF can be inverted to obtain the income level of a household with income rank h, that is, $y(h) = F^{-1}(h;\boldsymbol{\theta})$. This function can be used to derive the Lorenz Curve, i.e., fraction of total income earned by the bottom x% of the population,

$$L(x;\boldsymbol{\theta}) \equiv \frac{\int_0^x F^{-1}(h;\boldsymbol{\theta})\,dh}{\int_0^1 F^{-1}(h;\boldsymbol{\theta})\,dh}, \tag{9}$$

which subsequently feeds into the calculation of the Gini inequality coefficient:

$$G(\boldsymbol{\theta}) = 1 - 2\left(\int_0^1 L(x;\boldsymbol{\theta})dx\right). \tag{10}$$

The share of the population that is undernourished and in poverty respectively is the share of the population whose income is below the threshold income levels y^{pou} and y^{pov}:

$$PoU = F\left(y^{PoU};\boldsymbol{\theta}\right) \tag{11}$$

$$POV = F\left(y^{POV};\boldsymbol{\theta}\right) \tag{12}$$

We consider CDF's that satisfy the following conditions.

Assumption 1 (Growth is a rising tide that lifts all boats) *There exists at least one parameter θ_i that maps into income per capita, $\mu_y = g(\theta_i, \boldsymbol{\theta_{-i}})$ with $\frac{\partial \mu_y}{\partial \theta_i} = \frac{\partial g}{\partial \theta_i}$ and for which the following holds:*

$\frac{dF}{d\mu_y} = \frac{\partial F}{\partial \theta_i} / \frac{\partial \mu_y}{\partial \theta_i} < 0$ for all y.

Assumption 2 (Growth preserves the income distribution) *The CDF allows a closed form solution to the Gini coefficient, $G = G(\boldsymbol{\theta})$, but is not affected by the growth parameter θ_i, i.e., $\frac{\partial G}{\partial \theta_i} = 0$.*

Assumption 1 says that the probability distribution is controlled by at least one parameter that allows us to increase GDP per capita and shift the entire CDF to the right such that the fraction of undernourished (or poor) people unambiguously declines ("trickle-down growth"). This thought-experiment will look somewhat different for each distribution: for the normal distribution mean GDP per capita is identical to the location parameter μ, i.e., so that $\frac{\partial \mu_y}{\partial \mu} = 1$ and $\frac{\partial F}{\partial \mu_y} = \frac{\partial F}{\partial \mu} < 0$; for the log-normal distribution the mean is also controlled by the location parameter μ (but not exclusively) with $\frac{\partial \mu_y}{\partial \mu} = \mu_y$; and for yet other distributions such as the Pareto Type 1 CDF both a scale and shape parameter satisfy Assumption 1.

Assumption 2 says that the parameter used to induce GDP per capita growth should not affect the degree of Gini inequality. This ensures that the results from comparative statics on the relationship between income per capita growth and the PoU are not conflated by changes in the income distribution. This assumption of "neutral income growth" also narrows down the number of parameters that can be used to induce GDP per capita growth, as for some distributions more than one parameter may satisfy Assumption 1.[9]

In addition to their effects on the affordability of the food and poverty minimums ($\underline{Q}$ and $\underline{R}$), higher food prices may also affect food insecurity and poverty by boosting income per capita through windfall gains for farmers. To incorporate such an income effect, let us differentiate in a stylized manner between urban and rural economies. In the urban economy, as before, households have a claim on national income, as captured by the income distribution function. We assume that food prices do not affect income in the urban economy. In the rural economy, instead, the income distribution is an agricultural endowment distribution, i.e., it represents the heterogeneous claims that households hold to aggregate agricultural output or the total land endowment. Here higher food prices will boost household nominal income in proportion to each households' claim on the country's agricultural output. Let $\mathbb{1}(Rural)$ be an indicator function that's equal to one when the condition between brackets, i.e., the economy is rural, is satisfied, and zero when the economy is urban.

[9] In the examples below we use distributions for which only one parameter satisfies Assumptions 1 and 2.

Finally, for matters of convenience to simplify the comparative statics for urban and rural economies we assume any CDF to be "homothetic", a quality usually preserved for utility and production functions. We can formally summarize these assumptions:

Assumption 3 (Higher global food prices increase income only in rural economies) *In rural economies, but not in urban economies, household nominal income constitutes a claim on the agricultural endowment, i.e.,* $y(h) = p_F r_F(h)$ *and* $\mu_y = \int_0^1 y(h)dh = p_F R_F$ *where* $R_F \equiv \int_0^1 r_F(h)dh$*, such that* $\frac{d\mu_y}{dp_F} = \mathbb{1}(Rural)R_F$.

Assumption 4 (Eligible CDFs are homogeneous of degree zero in in y and μ_y.) *CDFs must satisfy* $F\left(\lambda y; \lambda \mu_y\right) = F(y; \mu_y)$*. For rural economies this implies:*

$$F\left(\frac{y}{p_F}; R_F\right) = F(y; p_F R_F) = F(y; \mu_y) \tag{13}$$

Two examples of CDFs satisfying Assumptions 1,2 and 4 are:

Example 1 *The income (or agricultural endowment) CDF is log-normal:*
$F(y; \mu, \sigma) = \Phi\left(\frac{ln(y)-\mu}{\sigma}\right) = \Phi\left(\frac{ln(\frac{y}{\mu_y})+\sigma^2/2}{\sigma}\right)$*, where* $\Phi(x)$ *is the standard normal distribution, and Gini is given by* $G = 2\Phi\left(\frac{\sigma}{\sqrt{2}}\right) - 1$.

Example 2 *The income (or endowment) CDF is Pareto-like:* $F(y; \mu, \rho) = \left(\frac{1}{1+\rho}\frac{y}{\mu}\right)^{1/\rho} = \left(\frac{1}{1+\rho}\frac{y}{\mu_y}\right)^{1/\rho}$*. Gini is given by* $G = \frac{\rho}{\rho+2}$.

2.2 Comparative Statics

Under Assumptions (1)-(4), we can then summarize the effects of changes in food prices and GDP per capita on the PoU in the following proposition. Note that the results for POV are analogous to the results for PoU with y^{POV} replacing y^{PoU}.

Proposition 1 (Income, food prices, and the PoU. General case.) *Differentiating PoU with re-*

spect to p_F, μ_y, and κ, we can then state the following the results using semi-elasticities:[10]

$$\frac{dPoU}{dp_F/p_F} = \left(f\left(y^{PoU}\right) \underset{(\pm)}{\frac{dy^{PoU}}{dp_F}} + \frac{\partial F}{\partial \mu_y} \underset{(0/-)}{\frac{d\mu_y}{dp_F}} \right) p_F \tag{14}$$

$$\frac{dPoU}{d\mu_y/\mu_y} = \left(\frac{\partial F}{\partial \mu_y} - f\left(y^{PoU}\right) \frac{\kappa}{1-\kappa} \right) \mu_y < 0 \tag{15}$$

$$\frac{dPoU}{d\kappa/\kappa} = f\left(y^{PoU}\right) \left(\frac{y^{PoU} - \mu_y}{1-\kappa} \right) \kappa \gtrless 0 \text{ for } y^{PoU} \gtrless \mu_y \tag{16}$$

(i) Higher food prices change the nominal income level needed to buy the minimum calorie intake. This changes the PoU in proportion to the share of people $f\left(y^{PoU}\right)$ that stand at the income threshold. In rural economies, the CDF also shifts to the right because higher food prices lead to windfall gains, subsequently raising GDP per capita. The overall effect of higher food prices is unclear.
(ii) Higher GDP per capita lowers the PoU by shifting the CDF to the right, and by increasing social benefits for households below average income.
(iii) an increase in the degree of income redistribution lowers the PoU provided income of the marginally food insecure household is below the mean.

Proof. Follows from Assumption (1)-(4) and inspection of the derivatives. See appendix.

Proposition 1 examines how changes in food prices and GDP per capita affect food insecurity. Our focus here is on the extensive margin of food insecurity, which considers the overall share of affected households (i.e., those below the threshold), rather than the intensive margin, which looks at the *degree* of insecurity within households as measured by their food consumption level. Consequently, the change in the PoU in response to income and food price fluctuations is shaped not only by parameters of the demand function (as is true for the intensive margin of food insecurity), but also by attributes of the income distribution. For example, a marginal increase in food prices affects food consumption for all households to some degree, but how many households will actually slide below the threshold as a result depends on the fraction of people $f(y^{PoU})$ that stand at said income floor.

Under quite general conditions, Proposition 1 tells us that while economic growth and

[10]We do this because our regression coefficients constitute semi-elasticities, see section 5.

larger social transfers unambiguously serve to lower the PoU, the effects of higher food prices are unclear. In order to obtain sharper predictions (even regarding the sign of the price elasticity), one must assume specific functional forms and put further restrictions on model parameters.[11] Furthermore, particularly sharp qualitative predictions can be obtained when preferences are further restricted to CES ($\varepsilon_F = \varepsilon_{NF} = 1$).[12] For ease of exposition we also mute the redistribution channel ($\kappa = 0$):

Proposition 2 (Income, food prices, and the PoU. CES case.) *Consider Example 2 with CES preferences. The closed-form solutions to the PoU and POV in urban and rural economies are:*

$$PoU_U = \left(\frac{1}{1+\rho}\frac{\tilde{\alpha}(p_F/P)\underline{\underline{Q}}}{R}\right)^{1/\rho} = f_U(\underset{+}{p_F}, \underset{-}{R}) \tag{17}$$

$$PoU_R = \left(\frac{1}{1+\rho}\frac{\tilde{\alpha}(p_F/P)\underline{\underline{Q}}}{(p_F/P)R_F}\right)^{1/\rho} = f_R(\underset{-/+}{p_F}, \underset{-}{R_F}) \tag{18}$$

$$POV_U = \left(\frac{1}{1+\rho}\frac{\underline{R} + \frac{p_F}{P}\lambda\underline{\underline{Q}}}{R}\right)^{1/\rho} = g_U(\underset{+}{p_F}, \underset{-}{R}) \tag{19}$$

$$POV_R = \left(\frac{1}{1+\rho}\frac{\frac{P}{p_F}\underline{R} + \lambda\underline{\underline{Q}}}{R_F}\right)^{1/\rho} = g_R(\underset{-}{p_F}, \underset{-}{R_F}) \tag{20}$$

Food insecurity:

(i) In the urban economy, the positive price elasticity of the PoU is equal to or strictly smaller than the negative income elasticity in terms of magnitude iff $\eta \leq 1$ (i.e., $\frac{PoU}{dp_F/p_F} \leq -\frac{dPoU}{dR/R} = \frac{1}{\rho}PoU < 0$).

(ii) In contrast, in the rural economy the food price elasticity of the PoU is positive only for $\eta > 1$, negative for $\eta < 1$, and zero for $\eta = 0$. The (agricultural) income elasticity of the PoU is identical to the income elasticity in the urban economy (i.e., $\frac{dPoU}{dR_F/R_F} = -\frac{1}{\rho}PoU < 0$).

Poverty:

(iii) In the urban economy, the food price elasticity of POV is positive (provided $\lambda > 0$) and the income elasticity is negative. For the food price elasticity of PoU to be larger in magnitude than the food price

[11] In the next section we will accomplish this by calibrating the model to country data to get quantitative predictions of the income and price elasticities.

[12] Novel insights into the price and income effects can also be gained when we adopt isoelastic nonhomothetic CES preferences ($\lambda = 0$). In this case, eqs.(45)-(48) in the appendix reveal that the responsive of food insecurity to food price changes hinges on the product of three critical factors, namely (i) the "mass" of poor people on the food insecurity threshold, (ii) the magnitude of the substitution elasticity relative to the income elasticity of food demand, and (iii) the degree of income redistribution.

elasticity of POV it is sufficient (but not necessary) that either $\eta \geq 1$ or $\lambda = 0$.
(iv) In rural economies, the income and price elasticities of POV are negative, i.e., both higher income and higher food prices serve to lower POV.

Proof. Follows from inspecting the derivatives of eqs.(17)-(20). See also the appendix.

Two qualitative predictions summarized in Proposition 2 are of particular interest. First, with CES preferences we can unambiguously sign the food price elasticity of the PoU. As it turns out, the food price elasticity is governed by at most three sub-effects: a positive price effect and an expenditure share effect ($\gtreqless 0$ for $\eta \gtreqless 1$) driving the demand for food, and a negative income effect for farmers (which is only present in rural economies). In the urban economy the food price elasticity is strictly positive as the price effect always dominates the expenditure share effect (which is negative when food and non-food are strict complements). In the rural economy, however, the income effect and the price effect perfectly offset each other, such that the expenditure share effect fully determines the sign of the food price elasticity.[13] If food and non-food goods are complements, the food price elasticity is negative. In the real world, which is probably a blend of the stylized urban and rural models, we can then postulate that the food price elasticity can be negative, positive, or close to zero.

Second, the food price elasticity of poverty is more difficult to sign than the food price elasticity of food insecurity, as the former may be either positive or negative in urban and rural contexts respectively. Heady and Martin (2016) provide a summary of recent empirical studies, indicating that higher food prices in the short term typically exacerbate food insecurity (e.g., Headey (2013)) but, paradoxically, contribute to a reduction in poverty (e.g., Headey and Hirvonen (2023), Headey (2018)). This is surprising, as poverty and food insecurity constitute two seemingly similar concepts. The framework here has shown, however, that in principle the concepts are still sufficiently different as to allow for opposite effects under realistic parameters values, i.e., $\eta \leq 1$; with higher food prices magnifying food insecurity but reducing poverty.

[13] In reality, the passthrough from global food prices to farmer income is likely to be substantially less than 1. For a sample of smallholder farmers from Ethopia, Kenya, and Malawi, Dhingra and Tenreyro (2021) find that the trickle down from higher world food prices to farmer income is less than 20 percent. More generally, intermediaries receive most of the gains from trade while farmers receive less than 1/3 of it. In addition, farmers' potential supply response in developing countries may be reduced due to liquidity constraints and limited access to critical farming inputs like fertilizers.

Proposition 3 (Inequality and the PoU.) *(i) Consider the LN CDF of Example 1. In this case, the PoU strictly increases with the degree of inequality if y^{PoU} falls short of the median income level and decreases otherwise* $\left(\frac{dPoU}{d\sigma/\sigma} = -\left(\frac{ln(y^{PoU})-\mu}{\sigma}\right)\Phi'\left(\frac{ln(y^{PoU})-\mu}{\sigma}\right) \gtreqless 0 \Leftrightarrow y^{PoU} \lesseqgtr e^{\mu}\right)$.
(ii) Consider the Pareto CDF of Example 2. In this case, the PoU increases with the degree of inequality iff the initial level of inequality is high enough (or the initial level of PoU is small enough), and decreases otherwise $\left(\frac{dPoU}{d\rho/\rho} \gtreqless 0 \Leftrightarrow PoU \lesseqgtr \overline{PoU} \equiv e^{-\frac{1}{1+\rho}}\right)$.

Proof. See appendix.

The effects of inequality on the PoU are summarized in Proposition 3. For both the log-normal and the Pareto distribution, it turns out that a decrease in inequality increases income of all households below a certain "inflection point" and decreases it for all households above the inflection point, while leaving GDP unchanged. As such, a reduction in inequality lowers food insecurity if and only if the marginally food insecure household stands below the income inflection point. Figure 1 illustrates, with a numerical example, the sensitivity of the PoU with respect to both income levels and inequality.

In addition to the key testable implications laid out in Propositions 2-3, the model makes predictions on how the semi elasticities of food prices and income per capita change with the level of per capita income and inequality:

Proposition 4 (Structural characteristics and the semi-elasticity of PoU to income.) *Consider again Example 2 with CES preferences. The responsiveness of the PoU to income:*
(i) can become greater or weaker at higher levels of income, i.e.,
$\frac{d}{d\mu_y}\left(\frac{dPoU}{d\mu_y/\mu_y}\right) = \frac{dPoU}{d\mu_y}\left(\frac{dPoU/PoU}{d\mu_y/\mu_y} + \frac{\kappa}{1-\kappa}\frac{\mu_y}{y^{PoU}}\right) \gtreqless 0 \Leftrightarrow \rho\kappa \lesseqgtr \frac{\tilde{\alpha}p_F Q}{\mu_y}$.
(ii) can become greater or weaker in countries with a higher degree of income inequality, i.e., $\frac{d}{d\rho}\left(\frac{dPoU}{d\mu_y/\mu_y}\right) \gtreqless 0 \Leftrightarrow PoU \gtreqless e^{-\frac{2+\rho}{1+\rho}}$.

Proof. See appendix.

Consider how the income elasticity of the PoU changes when income increases. There are two effects. On the one hand, there will be fewer households to push out of undernourishment at higher levels of income and so the income semi-elasticity weakens. On the other hand, the absolute amount of income redistribution increases at higher income levels. Proposition 4 (i) says that in theory the overall effect could go in either direction. Using parameter values representative of a low-income country, our model predicts that in practice the reaction of PoU to income growth tends to decline at higher levels of income (see figure 2), which we empirically confirm in section 6. Figure 2 also shows that the relation between the semi-elasticity and key parameters is highly non-linear.

The effect of inequality on the semi-elasticity of PoU to income is also ambiguous. There are two opposing effects. First, there is a "substitution" effect that reduces the impact of GDP growth on PoU because PoU increases with inequality ($\frac{dPoU}{d\rho} > 0$) and the income semi-elasticity declines with PoU. The second effect works in an opposite direction: when inequality is low an increase in GDP growth is more "inclusive", that is, in absolute terms it is more sizeable for poor households, thereby moving a greater mass of households around the food security threshold. Section 6 presents empirical evidence that the semi-elasticity is slightly stronger in more equal societies, which would suggest that the second effect dominates.

Our low-income country calibration exercise predicts that the semi-elasticitity of PoU to income should be weaker in more equal societies (see figure 2), which implies that the first effect dominates. Section 6 present empirical evidence in favor of this prediction. Table 1 suggests that the semi-income elasticity is weaker in societies with more equality, for which we present empirical evidence in section 6.

3 Model Calibration

We calibrate our model to match key macroeconomic data moments and targets. This calibration yields alternative estimates and bounds for income and price semi-elasticities of food insecurity, complementing our regression results. The calibration incorporates additional data not used in the regressions, including Gini coefficients, social protection spending, and external demand parameters.

3.1 Parameter Estimates

Two simple calibration exercises are considered. In the first, we work with Stone-Geary Cobb-Douglas (CD) preferences (thus imposing $\epsilon_F = \epsilon_{NF} = \eta = 1$) and assume that income is Pareto distributed (i.e., this is our Example 2). For our second calibration we stick with the Pareto income distribution, but on the consumer side we opt instead for isoelastic non-homothetic CES preferences.

Cobb-Douglas Calibration. The parameter ρ is set to match each region's Gini coefficient by using the Gini equation for the Pareto distribution, $G = \frac{\rho}{\rho+2}$. The household expenditure share on food, α, is based on that of a representative high-income country, i.e., Sweden, and comes from Haver Analytics. The parameter κ is set equal to social protection expenditure as a share of GDP in 2010 based on data from the IMF and World Bank while s_q is derived using GDP p.c. and our own estimate of the food component of the 2008 social poverty line figures (in 2011 PPP USD/day) for different income groups taken from Jolliffe and Prydz (2021). The parameter λ is set such that, given all the before mentioned parameters, eq.(17) matches each region's 2010 PoU; and, finally, the semi elasticity then follows from substituting the estimated parameter values into the expression for $\frac{dPoU}{d\mu_y/\mu_y}$.

Isoelastic CES Calibration. The following data points and parameters are identical to those of the Cobb-Douglas calibration: Gini, GDP p.c., ρ, κ, s_q, and PoU_0. Values for the parameters of the non-homothetic CES function are adopted from Nath (2023), that is, $\eta = 0.27$, $\epsilon_F = 0.29$, and $\epsilon_{NF} = 1.08$, where ϵ_{NF} is equated to the average income elasticity of the manufacturing and service sectors. Our estimate of the food budget share, m_{NF}, is based on the suggestion by Smith and Subandoro (2007) that households who are most vulnerable to food insecurity spend in excess of 75 percent of their income on food. The parameter bundle $\tilde{\alpha}$ (and thus λ) is then set such that eq.(17) matches each region's 2010 PoU; and, finally, the elasticities then follow from substituting the parameter estimates into eqs.(45)-(48) (see the appendix).

3.2 Predictions of Price and Income Semi-elasticities

Starting with Stone-Geary CD preferences, a simple calibration of the model's key parameters to different regions predicts a semi-elasticity of PoU to income (for both urban and rural economies) that ranges from -0.10 pp to -0.17 pp and on average equals about -0.12 pp (see table 1).[14] As the regression results in section 6 show, our preferred estimate of the semi-elasticity of PoU to income is close to that prediction. When preferences are CD, Proposition 2 tells us that for urban economies the food price elasticity is equal in magnitude to the income elasticity, but opposite in terms of sign. For rural economies, instead, the food price elasticity is zero (see Proposition 2). This calibration thus indicates that the country-level food price semi-elasticity ranges from 0 to 0.17 percentage points, dependent on whether the rural or urban economy model better represents aggregate responsiveness of food insecurity to food prices.

Next, consider our calibration with isoelastic non-homothetic preferences. As can be gleaned from table 2, we find that the semi income elasticity of the PoU in this case is identical to the CD case. While the parameter bundle $\tilde{\alpha}$ depends on additional parameters in the case of isoelastic non-homothetic preferences compared to CD preferences, the calibration itself depends only on the aggregate value of the parameter bundle, not its individual components, and thus the income elasticities of the PoU are the same regardless of the type of consumer preferences. The price elasticities of the PoU, however, depend directly on the values of e.g., the consumer income elasticities for food and non-food. Ultimately, the price elasticities for the urban economies still end up being quite close to the opposite of the income semi-elasticity. This is because the sign and magnitude of the food price elasticity of the PoU are tightly linked to the ratio $\frac{\eta-\epsilon_F}{\epsilon_F}$ (see eqs.(47)-(48) in the supplementary appendix). Since the income elasticity of food ϵ_F and the substitution elasticity η almost offset each other, that ratio ends up being close to zero just like the CD case (for which $\eta = \epsilon_F = 1$ and thus $\frac{\eta-\epsilon_F}{\epsilon_F} = 0$). This is an important finding because a naive researcher, armed with merely a CES specification and a reasonable prior that food and non-food are complements ($\eta < 1, \epsilon_F = \epsilon_{NF} = 1$), would end up predicting that the food price elasticity of the PoU should be negative (which contrasts with our findings in section 6).

[14] Our calibration approach efficiently uses regional aggregates to assess semi-elasticity values across varying income levels and inequality degrees.

3.3 Summary

We have presented a heterogeneous agent model with non-homothetic preferences and used it to study the role of food prices, income per capita, and income inequality in driving food insecurity (and poverty). The model rationalizes several empirical puzzles, including (i) why food insecurity is less sensitive to food prices than to income per capita (the reason being that farmers receive windfall income gains from higher food prices that offset negative affordability effects); and (ii) why ceteris paribus the effect of food prices on poverty is more significant compared to their effect on food insecurity (because poverty and food insecurity are different concepts and when it comes to poverty higher food prices may allow households to make more effective trade-offs between food and non-food needs). While some of these puzzles have been addressed separately in other studies, our model constitutes a unified and analytically tractable framework to examine them together. Finally, two calibration exercises give a sense of the magnitude of the price and income elasticity that one could expect to see in the data. The semi-elasticity of PoU to income should range between -0.10 and -0.17pp which implies that a doubling of income should lower the prevalence of undernourishment by 10-17pp, a very sizeable effect. In contrast, when food prices fall by a 100 percent this leaves the PoU roughly unchanged in rural economies and lowers it by 9-16 pp in urban economies.

4 Data and Descriptive Statistics

From a measurement perspective, we focus on objective manifestations of food insecurity related to qualitative adequacy and quantitative sufficiency of diets (Wilde, 2011). To capture aspects of diet quality, we use the share of dietary energy from cereals, tubers and roots and the average supply of animal protein measured in grams per capita per day. For the most severe manifestation of food insecurity related to insufficient caloric intake we use the Prevalence of Undernourished (PoU). The PoU is defined as the share of a country's population whose habitual food intake is insufficient to conduct an active and healthy life.

The PoU indicator as derived by FAO uses a log-normal probability density function for yearly dietary energy intake in the population, which requires the estimation of two parameters in order to fully characterize this distribution. The share of undernourished people in a country is then estimated as a cumulative probability of being below the minimum dietary energy requirements (MDER), i.e., the undernourishment threshold. More formally,

$$PoU = \int_{x<MDER} f(x|\Theta)\, dx \tag{21}$$

where $f(x|\Theta)$ is the log-normal distribution of caloric intake and Θ includes a location and a scale parameter. This function is intended to capture two dimensions of food security, namely food availability through the location (i.e., mean) parameter and differential food access through the higher moments (variance, skewness, and kurtosis). The mean is estimated every year from aggregate data on national food utilization accounts or from household survey data, when these are available. The other parameter and the MDER are estimated from micro data less frequently.

The literature has highlighted some limitations of the PoU, due to its top-down and aggregate approach. These limitations include the quality of the national food accounts data, the choice of a single undernourishment threshold for the whole country, and the lack of information on the severity of food insecurity. We refer the interested reader to FAO's technical documentation for a detailed discussion (Cafiero, 2014).

An alternative measure of food insecurity is the Food Insecurity Experience Scale (FIES), which overcomes the feasibility constraints faced by the PoU, as it does not require a costly dietary intake survey and the assumption of an undernourishment threshold. The main criticism against the FIES questions the comparability of perceived hunger experience across different individuals, countries and cultural contexts, while other authors highlight the possibility that it may overestimate food insecurity compared to insufficient-intake measures like the PoU (Barrett, 2010). We opt for the PoU as an objective and aggregate measure of national food insecurity, which has been selected by the United Nations to track progress towards the achievement of zero hunger by 2030. Further, the PoU has a much longer time coverage, spanning almost two decades, while the FIES is available only for three waves. This makes the PoU more suitable for our cross-country analysis on how food insecurity varies with business cycle fluctuations.

Data on GDP per capita and social protection expenditure come from the World Bank. We use real GDP per capita measured in constant 2015 dollars. Social protection expenditure in constant 2015 dollars includes current in-kind or cash transfers to households intended to provide for the needs that arise from social risks. They fall mostly under two broad categories: social security (e.g., unemployment benefits, retirement pension) and social assistance. Food inflation is defined as the year-on-year change in the food component of a country's Consumer Price Index and is taken from the global inflation database constructed by Ha et al. (2023).

Our estimation sample comprises 143 countries across all continents and income groups and spans a period between 2001 and 2021. Countries with missing observations in a given year for the dependent or independent variables were dropped from the sample. We also drop observations if in a given year the country has experienced a high food inflation episode of above 50%, or a strong deflationary episode (bottom 10% of all observations). Our final estimation sample is an unbalanced panel.

The top left graph of figure 3 shows the evolution of the PoU in the sample period by income group. Low-income countries show the most significant rates of undernourishment, with a 30% incidence compared to the global average of 10%. This gap with the rest of the world has widened in the recent decade.

The top right graph of figure 3 gives a descriptive view of the relationship between undernourishment and real GDP per capita. Undernourishment decreases with GDP per capita, but it also becomes less responsive to income growth as countries become richer.

Table 3 describes the independent variables used in this study. GDP growth in the developing world has outpaced that in high-income countries. The level of food inflation in developing countries at the beginning of the observation period was almost double the one observed in the rich world (column 5), providing suggestive evidence of a positive association between food prices and undernourishment. The next column shows a secular reduction towards lower food inflation in upper-middle-income and high-income countries. Inflation is also least volatile in the group of high-income countries.

5 Empirical Strategy

We are interested in estimating the relationship between aggregate food insecurity and its macroeconomic determinants. We can cast this relationship through a linear model:

$$y_{it} = \alpha + (\beta_0 + \gamma_i)t + \beta_1 X_{it} + u_i + \epsilon_{it}, \tag{22}$$

where y_{it} represents our measures of food insecurity for country i at time t, namely, the prevalence of undernourished, the share of dietary energy from cereals, roots and tubers, and animal protein supply. On the right-hand side of equation (22) the matrix X_{it} includes our two main macro drivers, i.e., log real GDP per capita and food inflation (annual percentage change of the food component of the Consumer Price Index), as well as global and country time effects to control for phenomena that impact all countries in a similar fashion (t). The composite error term includes country-specific time-invariant unobserved heterogeneity (u_i) to capture geographical, historical or slow-changing institutional factors and a mean zero idiosyncratic shock (ϵ_{it}).

We adopt a first difference instrumental variables (FD-IV) estimation approach, to address concerns over omitted variables and reverse causality–which could lead to biased estimates from endogenous co-variation between the composite error term and the controls. In our setting, time-invariant unobservables (u_i) may be correlated not only with food insecurity but also with the GDP and other right-hand side variables, potentially confounding the relationship. Taking the first difference of equation (22) eliminates u_i, excluding the possibility of bias from correlation of X_{it} with time-invariant confounders. This also allows to cast the relationship in terms of rates of change, since we are mostly interested in the short-term variations of food insecurity along the phases of the business cycle. It removes possible unit roots in the variables, making sure we are using stationary variables on both sides of the equation to avoid spurious findings. Finally, we utilize changes in food inflation rather than levels to net out the influence from monetary factors:[15]:

$$\Delta y_{it} = \beta_0 + \theta y_{i0} + \beta_1 \Delta X_{it} + \Delta \epsilon_{it}, \tag{23}$$

where we assumed that $\gamma_i = \theta y_{i0}$ to capture a time-invariant regressor that controls for initial conditions allowing us to investigate whether there is convergence among countries towards

[15]Levels of inflation are often correlated with long-term trends and underlying factors such as institutional quality. Poor institutions and weak state capacity can contribute to both high food inflation and food insecurity through inadequate control over monetary conditions and economic instability. By using changes in inflation, we mitigate the effects of these persistent weaknesses, focusing instead on sudden shifts in the monetary policy stance and inflation expectations (which often occur in response to external shocks). This approach also aligns with the principle that when agents are forward-looking, wages typically reflect anticipated inflation (at least to some degree), which attenuates the impact of steady food inflation. Consequently, inflation changes, which would incorporate inflation surprises, more directly lead to unexpected deviations in purchasing power and, thus, food insecurity.

some "equilibrium level" of food insecurity.[16] Countries that start out from higher levels of food insecurity should exhibit a faster pace of catching up.

Endogeneity may also stem from correlation of the controls with the idiosyncratic shock even after having netted out u_i. This situation is often pervasive in a macro setting and potentially more problematic. For example, a given year's shock to food security may feed back into next year's fiscal budget as governments react quickly to distress situations by scaling up social protection spending, which in turn affects growth and prices (*reverse causation*). As a result, we may end up capturing a smaller (i.e. closer to zero) reaction of food insecurity to GDP growth than we would have in absence of this feedback effect. A similar result would be obtained for the coefficient of food inflation if governments reacted by introducing price controls for food items. All these scenarios invalidate the strict exogeneity assumption, which requires the error term to be uncorrelated with past, current and future values of the covariates ($E[\Delta\epsilon_{it}|X_{is}] = 0$ for $s = 1, 2..t..T$). The resulting least squares estimates of equation (23) would be biased towards zero.[17]

We use external instruments for each endogenous variable to isolate plausibly exogenous variation. We instrument income growth with the average growth rate of a country's trading partners and the change in the commodities terms of trade (Acemoglu et al., 2008; Burke, 2012). In the average growth rate of trading partners the year-specific weights are given by the share in the previous three years of the country's export to a given trading partner on total exports during the same period. For the second instrument of growth we use IMF's commodity terms-of-trade (CTOT) index, which is the average of a range of commodity prices, each of which is weighed by the country's share of net exports of a given commodity on its GDP over the previous three years (Gruss and Kebhaj, 2021). (Details on the instruments are provided in the appendix).

Finally, food inflation is instrumented with a regional and a global (or "rest-of-world") harvest shock. We use a Hodrick-Prescott filter to extract regional and global deviations from

[16]A linear model as shown here, using the PoU in changes and GDP per capita in log-differences, can be obtained by applying a first-order Taylor approximation to eq.(17).

[17]The direction of reverse causality bias is hard to predict *a priori*. It depends on the sign and strength of the effect of a given covariate on the dependent variable and of the reverse effect of the dependent variable on the covariate. Based on assumptions on the mutual relationship between variables that we deem reasonable, here we envisage a positive bias for income , which in the context of an inverse relationship between food insecurity and these covariates, implies coefficients biased towards zero. For food inflation, which positively affects food insecurity but may be negatively affected by it through price controls, the bias could be negative, thus attenuating the effect towards zero.

per capita trend production of (the calorie-weighted sum of) four grains - wheat, corn, soybeans, rice - which jointly provide more than two thirds of calories for human consumption, either directly or indirectly as livestock feedstuff. The regional supply shock for country i represents the percentage deviation from per capita trend production across all countries within the region, except country i. The rest-of-world shock for country i represents the percentage deviation from total per capita trend production in all countries outside the country's own region. To aggregate by region we follow the World Bank classification, which distinguishes between 7 regions: East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and Caribbean (LAC), Middle East and North Africa (MENA), North America (NA), South Asia (SA), and Sub-Saharan Africa (SSA). In the next section, we provide evidence of instrument relevance ($E[X_{it}|Z_{it}] \neq 0$) and validity ($E[\Delta\epsilon_{it}|Z_{is}] = 0$ for $s = 1, 2..t..T$).

6 Results

This section presents the regression results for the PoU. Results for qualitative aspects of food insecurity (i.e., energy share of staples and protein consumption) are presented in an online supplementary appendix to conserve space. We focus on PoU in the main text as it is the primary indicator of food insecurity.

Table 4 shows the estimated coefficients for equation (23). The FD estimate of the marginal effect of income growth indicates that the PoU declines by roughly 0.05 percentage points (pp) for every 1 pp increase in the GDP per capita growth rate, which, in relative terms, amounts to a 0.37 percent reduction (column 1).[18] This result is similar to Soriano and Garrido (2016), who find that a 1 pp increase in GDP per capita growth reduces PoU by 0.29 percent. When endogeneity is ignored, our results for income are similar to those found in previous articles that do not address the issue. Our OLS estimate of food inflation is also statistically significant and amounts to an increase of 0.011 pp in undernourishment, considerably smaller than the effect of income.[19] Headey (2013) finds that a measure of subjective food insecurity declines by 0.12-0.24 pp (0.47%-1.25%) for a 1 pp increase in the real GDP

[18] Since both the outcome and growth are expressed as percentages in decimal format, the coefficient indicates the change in the outcome, measured in its own units, resulting from a one-unit change in the regressor, equivalent to 100 percentage points.

[19] Growth and food inflation have a similar standard deviation thus their marginal effects can be compared directly.

per capita growth rate, while a 1 pp increase in relative food inflation increases undernourishment by 0.1-0.2 pp. Their work uses a different measure of food insecurity, which limits comparability to our results.

Instrumental variable estimates (column 2, Table 4) have the same signs as the OLS ones, but the magnitudes of all effects increase by at least a factor of 2. A 1 pp increase in income per capita growth leads to an approximately 0.11 pp reduction in the share of undernourished, which in relative terms translates into a 0.79 percent reduction. Food inflation also has a significant effect on undernourishment, but the effect is smaller than the effect of growth. For every 1 pp acceleration in food inflation, the share of undernourished increases by 0.06 pp (0.46 percent). We are unable to place this estimate in a range of plausible magnitudes since we are unaware of previous work on the effects of food inflation on the prevalence of undernourishment. In a typical year, with a sample standard deviation of 0.043 for GDP growth and 0.058 for inflation changes, a one standard deviation increase in GDP growth would lead to an estimated 3.4% reduction in undernourishment. In contrast, a one standard deviation increase in food inflation would result in an approximate 2.7% increase in the share of undernourished. The results on the sign of the effects of growth align with the model predictions summarized in propositions 1 and 2. We discus below the result on the sign and magnitude of the food inflation effect relative to that of income.

Finally, we find that countries that start out with higher levels of undernourishment at the beginning of our observation period exhibit, all things equal, a higher reduction rate. Starting out with a 1 pp higher PoU implies a faster reduction in PoU by 0.02 pp per year. This convergence effect is significant in both estimation approaches.

Standard diagnostic tests for the first and second stage show that our instruments are both strong predictors of the endogenous variables and uncorrelated with the error term. Results for the first stage (table 5) show that our instruments have the expected sign and can induce variation in the endogenous variables. Current growth in trading partners is found to affect growth in the country of interest. Furthermore, improvements in the CTOT, stemming from increased (or decreased) prices of commodities that the country predominantly exports (or imports), positively affect short-term income growth. An F-test rejects the null hypothesis that the coefficients of the exclusion restrictions are jointly zero. For food inflation, we find that positive harvest shocks ease pressure on food prices, in line with our priors.

The validity of our instruments hinges on their independence from the error term in equation 23. The growth of a country's trade partners and shifts in its terms of trade predominantly stem from external forces, minimizing the likelihood of feedback from domestic macroeconomic factors, let alone undernourishment. We posit that these instruments influence undernourishment solely via their impact on the nation's GDP per capita growth and food inflation, rather than through hidden pathways that might contribute to the error term in our structural equation. This assertion gains strength when acknowledging that time-invariant or slow-moving variables such as institutional quality, which could correlate with the trading partners' institutional capacity, have been netted out through first differencing.

As for harvest shocks, we argue that the trend in grains production reflects (slow moving) fundamentals of supply and demand. Deviations from this trend, identified using a Hodrick–Prescott filter, are likely indicative of external shocks outside of farmers' controls, such as weather variability. The Hansen test statistics for instrument validity and the corresponding p values are reported in the last line of table 4. We cannot reject the null hypothesis (p-value $\approx$ 0.16) that our instruments are uncorrelated with unobserved drivers of food insecurity. These test results guarantee the consistency of the IV estimates.

Our results align with previous studies that use trade partners' growth and commodity terms of trade changes as instruments for domestic growth, finding them to be both relevant and valid (Burke, 2012). Finally, a Hausman test of endogeneity for ΔX based on the comparison of the FD *vis-à-vis* FD-IV sets of estimates did not provide sufficient evidence in favor of the null hypothesis that the potentially endogenous regressors can actually be treated as exogenous (p value = 0). Considering this and the reliability of the instruments, FD-IV is our preferred set of estimates.

Further, we re-estimate equation 23 after adding the absolute change in social protection expenditure (% of GDP) as a control. This variable has a large number of missing values. Considering the big reduction in estimation sample size that this implies, FD and FD-IV results for this specification are shown separately in table 6 and are not comparable to those of the baseline specification. FD estimates are in line with the model prediction, with social protection having a significant containing effect on undernourishment, although with a less steep gradient compared to that of income and food inflation.

The FD-IV estimates are based on the same set of instruments as before with the addition of age dependency ratio in the population as a dedicated instrument for social protection expenditure. The latter may drive social protection spending through its effect on the social security component (e.g. old age pensions). The FD-IV estimate of the social protection effect is considerably larger and still significant. While GDP growth and inflation have a similar scale, to be able to gauge the relative strength of social protection, we scale up its marginal effect by a factor of 4, which is the ratio of its standard deviation to that of the other two regressors. With this adjustment, a typical change in social protection expenditure leads to a reduction in undernourishment of 0.01 pp, less than a sixth of the inflation effect. However, the evidence on the effects of social protection is weak, at best, since first stage F statistics are lower and there is insufficient support for the validity of the instruments' set.

6.1 Unpacking the effects of growth and inflation

We investigate heterogeneity of the short-term effects of food inflation and growth along selected structural characteristics of the economy by introducing interaction terms in our baseline specification.

$$\Delta y_{it} = \beta_0 + \theta y_{i0} + \beta_1 \Delta X_{it} + \beta_2 W_{it} + \beta_3 \Delta X_{it} W_{it} + \Delta \epsilon_{it} \tag{24}$$

where W_{it} includes the mediating variables in levels. In one specification, we interact food inflation with the share of agricultural GDP, to investigate empirically the qualitative prediction of proposition 2 of our theoretical framework. In an alternative specification, to provide empirical support to propositions 3 and 4, we interact growth with GDP per capita and the income share held by the bottom 20%, which capture a country's stage of economic development and the state of income inequality, respectively.

Equation (24) is estimated with the same FD-IV approach as equation (23). The inclusion of level variables poses a bigger threat to the exogeneity assumption, since in the long run a country's level of income, for instance, is more likely to be both a determinant of undernourishment and diet composition and be affected by these variables in turn (Fogel, 2004). In this case, we resort to an alternative set of external instruments for the level variables W_{it}, which is sourced from the literature and includes contemporaneous and one year lag of the average seasonal temperature levels and the old age dependency ratio in the population. These are added to the instruments for ΔX_{it}. The same set of instruments is employed whether W_{it} comprises the share of agricultural GDP alone or metrics of GDP per capita and inequality.

Our baseline findings showed that the impact of food inflation is positive and less pronounced compared to income growth. This could be attributed to the fact that while higher food prices unequivocally intensify food insecurity in urban economies, their effect may be quite small and potentially even negative in rural economies, because unlike urban residents rural populations may actually benefit from higher food prices in the form of an income effect due to their involvement in market-oriented agriculture (see Proposition 2). To see if we could find support for this hypothesis, we explored whether the impact of food inflation on the PoU diminishes in proportion to the share of agricultural GDP. Figure 4 shows the FD-IV total effect of food inflation on undernourishment as a function of the share of agricultural GDP: $\beta_3(W) = \beta_1 + \beta_3 W$. The declining pattern provides some support for the model's prediction, but it is only suggestive considering that the interaction term is statistically insignificant (table 7). However, power to detect significant interaction effects in a model is much smaller than for main effects, requiring a larger sample size.

We conclude that the detrimental but smaller impact of food inflation compared to income growth can be explained in at least two ways. First, it suggests that the estimated effect of food inflation on aggregate food insecurity may constitute some average of the hypothesized larger urban effect and the smaller (or even negative) rural effect. Second, it may be indicative of other underlying microeconomic factors that limit farmers' benefits from higher prices, including the extent to which farm producers tap into domestic and international trade and how the aggregate gains are distributed between farmers and intermediate traders. These aspects deserve further investigation and are left for future research.

Further, the relationship between food insecurity and the GDP cycle can change over time as countries become richer or slowly adjust their structural characteristics. To see how the effects of growth vary with a country's characteristics, in figure 5 we plot the FD-IV total effect of growth against the GDP per capita level (left panel) and inequality measured through the share of income held by the bottom 20%. Underlying estimates are shown in table 8. First stage F tests reject the null hypothesis that the coefficients of the excluded instruments are jointly zero for all regressors. The Hansen test cannot reject the null hypothesis of exogeneity. Hence, we are confident about the overall consistency of the FD-IV estimates.

The left graph of figure 5 shows that undernourishment reacts to business cycle fluctuations for a broad range of income values (point-wise estimates are statistically significant through an income level of USD 20 thousand). Economic growth plays an important role in reducing hunger, especially at the early stages of development, but becomes less effective as countries grow richer and undernourishment plunges to low levels. This implies that the long term relationship between undernourishment and income is non-linear. This confirms the conclusions drawn from the descriptive analysis of figure 3. For LICs that are still at the early stages of development undernourishment declines rapidly as income grows. For the HICs the curve is considerably less steep as income increases lead to smaller reductions in hunger. The higher income elasticity of hunger in middle- and low-income countries relates also to a larger share of the population that is closer to the undernourishment threshold and that is shifted above or below the threshold as income oscillates.

The right graph shows that income growth effectiveness in reducing hunger increases with inequality, although the gradient is small and significant only at some portions of the range of the income held by the bottom 20%. We interpret this in the light of our framework, which predicts this situation when the 'substitution' effect is almost completely offset by the direct effect, i.e., more inequality implies a higher PoU, which mechanically reduces the growth semi-elasticity of the PoU, all else constant. Moreover, Proposition 3 predicts a direct relationship between food insecurity and inequality. The total effect of inequality is sizable (table 8), with an increase of 1 pp in the income share of the bottom 20% reducing the PoU by 0.1 pp (-0.147 + 1.857*0.024, where 0.024 is the sample average of growth), although it is imprecisely estimated (se 0.323).

6.2 Sensitivity analysis

We conduct several robustness checks concerning the reliability of our instruments and the specification of the controls. To save on space, results of the robustness checks are provided only for the analysis of PoU.

First, we check the sensitivity of our estimates to changes in the instruments set by replacing global harvest shocks with regional ones. Results for the second stage shown in table 9 look very similar to those of our benchmark specification. The first stage estimates (table 10) are also similar to the baseline specification with the regional shock having a smaller coefficient although still significant. Considering the ever integrated nature of grains markets, we would expect global shocks to have a greater influence on food inflation. We cannot reject the null hypothesis of instrument validity.

Second, the uptick in global food insecurity over the last decade is driven by low-income countries, particularly in Sub-Saharan Africa. One potential reason is a surge in armed conflicts (FAO, 2018; Andree et al., 2020). To shed light on this hypothesis, we include a dummy variable that equals 1 if country i was involved in an armed conflict in a given year. The dummy accounts for both conflicts occurring between two or more states as well as internal conflicts between the government of a state and one or more internal opposition groups. This variable comes from the Uppsala Conflict Data Program, while we use publicly available information to determine the territory on which fighting took place. Only conflicts with at least 1000 battle-related deaths in a given year are considered (see Davies et al. (2022)).

Estimates of equation 23 with the armed conflict dummy are shown in table 11.[20] Only the FD estimate of the armed conflict effect is positive and statistically significant but not sizable (even accounting for scale, sd=0.35). After controlling for armed conflict, the effect of income growth and inflation are similar to the baseline estimates both for the FD and FD-IV model. For the latter, diagnostic tests indicate that the instruments are well correlated with the endogenous regressors and uncorrelated with the error term in the main equation. Thus, armed conflicts do not seem to have a direct effect on aggregate undernourishment and controlling for them leaves the coefficients of growth and inflation unchanged. Hence we conclude that at the macro level they might exert their influence only indirectly through income and food price channels.

7 Discussion

Following the Covid-19 pandemic and the global food price rally in the wake of Russia's invasion of Ukraine, food insecurity has moved back to the top of the policy agenda of the interna-

[20] We consider armed conflict to be exogenously determined with respect to unobserved determinants of the PoU and do not instrument it.

tional community.[21] While an in-depth reflection of how the international policy community and domestic policymakers reacted to the ongoing global food security crisis is beyond the scope of this paper, we observe that calls by international organizations to address the recent crisis have rested on a wide range of ideas, including (i) boosting agricultural production, (ii) a strengthening of safety nets for the most vulnerable, (iii) investing in climate resilient agriculture, and last but not least (iv) facilitating international free trade in food. All proposals are consistent with the importance of income growth in tackling food insecurity, even though they do not directly refer to (macroeconomic policies that can foster) inclusive economic growth. All proposals, except (ii), are linked directly to the idea that to lower food insecurity it is imperative to bring down food inflation.

Overall, this balance of policies seems mostly appropriate considering our empirical findings, but there is room for improvement. In our view, perhaps too much of the policy debate has revolved around fighting food inflation. We conjecture this is in part because policy makers typically rely on a mental model of food insecurity that is centered around purchasing power (for certain groups), i.e., the intensive margin of food insecurity. This mental model has appeal not only because urban middle class discontent about purchasing power played an important role throughout history as a catalyst for political change and conflict (e.g., during the Arab Spring), but also because policymakers often engage with the issue of higher food prices primarily from the perspective of consumers rather than that of farmers.[22] However, the UN Sustainable Development Goals are framed around the PoU, the metric used in this paper that measures the fraction of households whose calorie intake is insufficient. This metric compels policymakers to devise strategies that elevate the most vulnerable households above said threshold.

This paper has demonstrated that fostering economic growth is the most effective strategy for tackling food insecurity, closely followed by reining in food inflation. In light of this, policymakers should revise their understanding of the drivers of food insecurity and prioritize policies that promote inclusive growth by guaranteeing equal opportunities for everyone and those with disadvantaged backgrounds in particular and by implementing redistribution. In-

[21] According to WEF (2022), livelihood crises is one of the global risks that increased the most since the start of the Covid-19 crisis, second only after worries over social cohesion erosion.

[22] Globally, only about one quarter of the world's population is employed in agriculture, but this number is as low as 1-4 percent in advanced economies (Roser, 2023).

deed, we find some evidence that inequality reduces the positive impact of economic growth on food security. They should also allow global food price increases to trickle down to domestic prices while enhancing targeted social protection within fiscal limits. This strategy would encourage sufficient food production, increase the incomes of food-insecure farmers, and protect the purchasing power of vulnerable urban households. It is important, however, to assess this strategy on a case-by-case basis, as some countries may have limited capacity to flexibly adjust their social protection systems to increase coverage or modify the size of transfers based on specific needs or episodes.

References

Acemoglu, P., S. Johnson, J. A. Robinson, and P. Yared (2008). "Income and Democracy". *The American Economic Review* 98.3, pp. 808–842.

Andree, P J, A Chamorro, A Kraay, P Spencer, and D Wang (2020). "Predicting Food Crises." *World Bank. Policy Research Working Paper* 9412.

Barrett, C. B (2010). "Measuring food insecurity". *Science* 327.5967, pp. 825–828.

Bogmans, Christian, Andrea Pescatori, and Ervin Prifti (2021). *Income versus prices: how does the business cycle affect food (In)-security?* IMF working papers. International Monetary Fund.

Borjas, G. J (2004). "Food insecurity and public assistance". *Journal of Public Economics* 88.7-8, pp. 1421–1443.

Burke, P. J. (2012). "Economic Growth and Political Survival". *The B.E. Journal of Macroeconomic* 12.1.

Cafiero, C (2014). "Advances in hunger measurement. Traditional FAO methods and recent innovations".

Comin, Diego, Danial Lashkari, and Martí Mestieri (2021). "Structural change with long-run income and price effects". *Econometrica* 89.1, pp. 311–374.

Darvas, Zsolt (2019). "Global interpersonal income inequality decline: The role of China and India". *World Development* 121, pp. 16–32.

Davies, Shawn, Therese Pettersson, and Magnus Öberg (2022). "Organized violence 1989-2021 and drone warfare". *Journal of Peace Research* 59.4.

De Winne, Jasmien and Gert Peersman (2021). "The adverse consequences of global harvest and weather disruptions on economic activity". *Nature Climate Change* 11.8, pp. 665–672.

Dhingra, Swati and Silvana Tenreyro (2021). "The rise of agribusinesses and its distributional consequences".

D'Souza, A and D Jolliffe (2014). "Food insecurity in vulnerable populations: coping with food price shocks in Afghanistan". *American Journal of Agricultural Economics* 96.3, pp. 790–812.

FAO (2018). "Building climate resilience for food security and nutrition". *The State of Food Security and Nutrition in the World 2020*.

— (2023). *FAOSTAT Food Balances*. License: CC BY-NC-SA 3.0 IGO. Extracted from: https://www.fao.org/ Data of Access: September 5, 2023.

FAO, IMF, WBG, WFP, and WTO (July 2022). *Joint Statement by the Heads of the Food and Agriculture Organization, International Monetary Fund, World Bank Group, World Food Programme, and World Trade Organization on the Global Food Security Crisis*. https://www.imf.org/en/News/Articles/20 IMF Press Release No. 22/259.

Fogel, R. W (2004). "Health, nutrition, and economic growth". *Economic Development and Cultural Change* 52.3, pp. 643–658.

Gilley, Otis W and Gordon V Karels (1991). "In search of Giffen behavior". *Economic Inquiry* 29.1, pp. 182–189.

Gregory, C. A and A Coleman-Jensen (2013). "Do high food prices increase food insecurity in the United States?" *Applied Economic Perspectives and Policy* 35.4, pp. 679–707.

Gruss, B. and S. Kebhaj (2021). "Commodity Terms of Trade: A New Database". *IMF working paper* WP/19/21.

Gundersen, C, J Pepper, and B Kreider (2011). "The Economics of Food Insecurity in the United States". *Applied Economic Perspectives and Policy* 33, pp. 281–303.

Ha, Jongrim, M Ayhan Kose, and Franziska Ohnsorge (2023). "One-stop source: A global database of inflation". *Journal of International Money and Finance*, p. 102896.

Headey, D. D (2013). "The impact of the global food crisis on self-assessed food security". *The World Bank Economic Review* 27.1, pp. 1–27.

Headey, Derek and Kalle Hirvonen (2023). "Higher food prices can reduce poverty and stimulate growth in food production". *Nature Food*, pp. 1–8.

Headey, Derek D (2018). "Food prices and poverty". *The World Bank Economic Review* 32.3, pp. 676–691.

Heady, Derek and William J. Martin (2016). "The Impact of Food Prices on Poverty and Food Security". *Annu. Rev. Resour. Econ.* 8, pp. 329–351.

Jensen, Robert T and Nolan H Miller (2008). "Giffen behavior and subsistence consumption". *American Economic Review* 98.4, pp. 1553–77.

Jolliffe, Dean and Espen Beer Prydz (2021). "Societal poverty: A relative and relevant measure". *The World Bank Economic Review* 35.1, pp. 180–206.

Lancaster, Kelvin J (1966). "A new approach to consumer theory". *Journal of Political Economy* 74.2, pp. 132–157.

Mahler, Daniel Gerszon, R Andres Castaneda Aguilar, and David Newhouse (2021). "Nowcasting Global Poverty". *Policy Research Working Paper;No. 9860.*

Matsuyama, Kiminori (2019). "Engel's law in the global economy: Demand-induced patterns of structural change, innovation, and trade". *Econometrica* 87.2, pp. 497–528.

Nath, Ishan (2023). "Climate change, the food problem, and the challenge of adaptation through sectoral reallocation".

Ravn, Morten O and Harald Uhlig (2002). "On adjusting the Hodrick-Prescott filter for the frequency of observations". *Review of economics and statistics* 84.2, pp. 371–376.

Roberts, Michael J and Wolfram Schlenker (2013). "Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate". *American Economic Review* 103.6, pp. 2265–2295.

Roser, Max (2023). "Employment in Agriculture". *Our World in Data*. https://ourworldindata.org/employ in-agriculture.

Salois, Matthew J., Richard Tiffin, and Kelvin G. Balcombe (2012). "Impact of Income on Nutrient Intakes: Implications for Undernourishment and Obesity". *The Journal of Development Studies* 48.12, pp. 1716–1730.

Smith, Lisa C and Ali Subandoro (2007). *Measuring food security using household expenditure surveys*. Vol. 3. Intl Food Policy Res Inst.

Soriano, B and A Garrido (2016). "How important is economic growth for reducing undernourishment in developing countries?" *Food Policy* 63, pp. 87–101.

Tiwari, S, S Daidone, M Ruvalcaba, E Prifti, S Handa, B Davis, O Niang, L Pellerano, P.Q van Ufford, and D Seidenfeld (2016). "Impact of cash transfer programs on food security and nutrition in sub-Saharan Africa: A cross-country analysis". *Global Food Security* 11, pp. 72–83.

WEF (2022). *The Global Risks Report 2022. 17th edition.* Tech. rep. World Economic Forum.

Wilde, P (2011). "Food security policy in developed countries". *The Oxford Handbook of the Economics of Food Consumption and Policy* 321.

Appendix A: Tables and figures

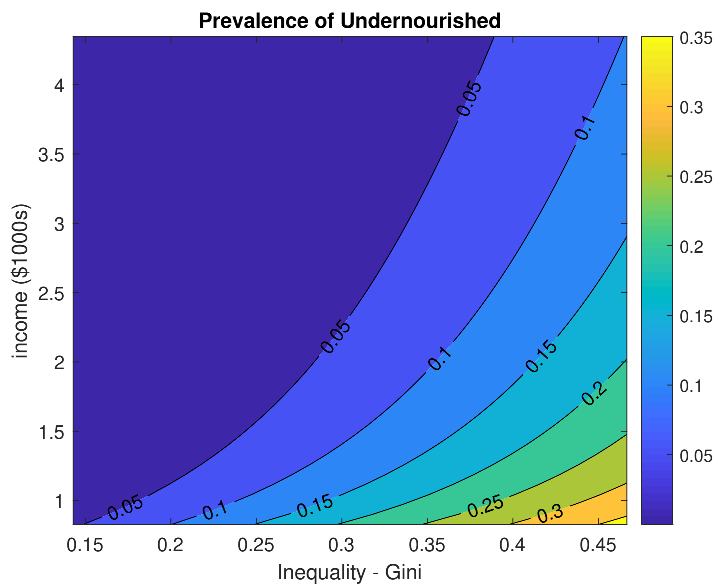

Figure 1: The effects of income per capita and Gini inequality on the PoU. Figure drawn for $\eta = \epsilon_F = \epsilon_{NF} = 1$, $\alpha = 0.14$, $\underline{C_F} = 0.5$, $\kappa = 0.05$, $\lambda = 0.97$, and with p_F chosen such that $s_q \equiv \frac{p_F Q}{\mu_y} = 0.14$ for $\mu_y = 2.5$.

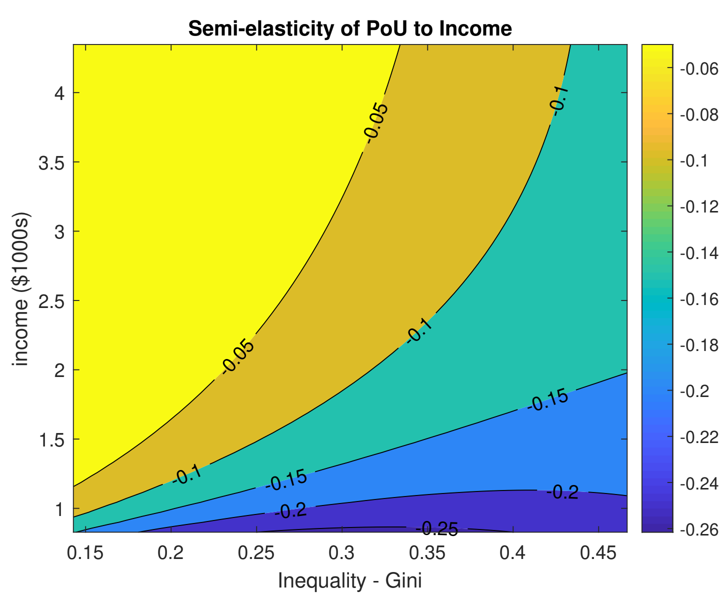

Figure 2: The sensitivity of the semi-elasticity of PoU to income with respect to income and inequality. Figure is drawn for the same low-income country parameter values selected for figure 1.

Table 1: Income (and food price) elasticity of the PoU. Cobb-Douglas preferences.

	Gini	GDP p.c.	ρ	α	λ	κ	s_q	PoU_0	$\frac{dPoU}{d\mu_y/\mu_y}$
Africa	0.47	2,484	1.77	0.14	0.97	0.05	0.14	0.17	-0.137
East Asia & Pacific	0.41	14,406	1.37	0.14	0.99	0.06	0.13	0.09	-0.110
Western Europe	0.30	43,790	0.84	0.14	0.55	0.18	0.07	0.03	-0.110
Eastern Europe & C. Asia	0.31	14,827	0.91	0.14	0.82	0.12	0.09	0.03	-0.098
Latin America & Carib.	0.45	6,773	1.65	0.14	0.93	0.10	0.11	0.11	-0.168
U.S. & Canada	0.37	47,958	1.16	0.14	0.69	0.12	0.05	0.03	-0.121

[a] **Note**: GDP p.c. (in constant 2015 USD) is the region average for 2010 and is taken from the World Bank ICP database; Gini is the region average 2010 Gini coefficient and is collected from Darvas (2019); PoU_0 is the region's average 2010 PoU. Reported values of κ, s_q and PoU_0 also represent region averages, i.e., unweighted averages across all countries within each region, subject to data availability. Parameter selection and estimation are described in the main text.

Table 2: Income and food price elasticities of the PoU. Isoelastic non-homothetic CES preferences.

	$\frac{dPoU_U}{d\mu_y/\mu_y}$	$\frac{dPoU_U}{dp_F/p_F}$	$\frac{dPoU_R}{dp_F/p_F}$
Africa	-0.137	0.130	-0.001
East Asia & Pacific	-0.110	0.104	0.001
Western Europe	-0.110	0.105	0.005
Eastern Europe & C. Asia	-0.098	0.093	0.004
Latin America & Carib.	-0.168	0.159	0.006
U.S. & Canada	-0.121	0.115	0.008

[a] **Note**: Except for the parameter values of the isoelastic CES function, which are adopted from Nath (2023), all data points and parameters used are identical to those of the CD calibration presented in Table 1. See explanation in the main text.

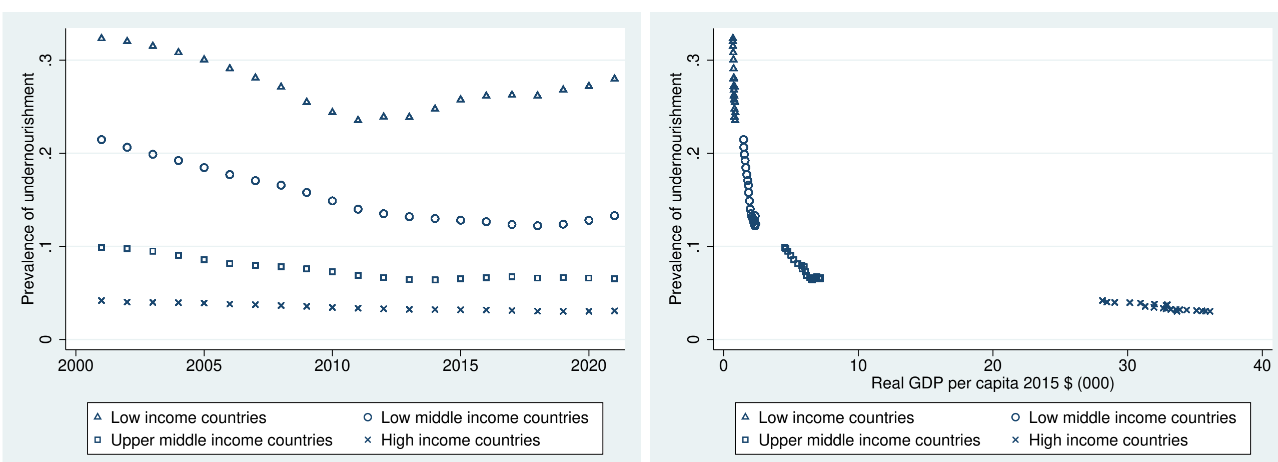

Figure 3: (A) Evolution of PoU over time and by income group (B) Relationship between undernourishment and GDP per capita by income group.

Table 3: Descriptive statistics: controls and instruments

	GDP_0	$\Delta ln(GDP)$	SP_0	ΔSP	FI_0	ΔFI	g^x	CTOT	$\Delta ln(CTOT)$
LIC	0.702	0.021	0.001	-0.000	0.082	0.001	0.018	95.787	0.002
	(0.559)	(0.058)	(.)	(0.014)	(0.057)	(0.088)	(0.057)	(5.555)	(0.017)
LMC	1.519	0.026	0.061	0.001	0.069	0	0.021	93.859	0.004
	(0.746)	(0.044)	(0.062)	(0.016)	(0.074)	(0.069)	(0.032)	(7.242)	(0.031)
UMC	4.608	0.027	0.059	0.001	0.085	-0.000	0.018	90.318	0.005
	(1.818)	(0.056)	(0.036)	(0.008)	(0.093)	(0.064)	(0.026)	(10.424)	(0.033)
HIC	29.101	0.018	0.136	0.001	0.037	-0.002	0.022	95.218	0.003
	(19.344)	(0.048)	(0.049)	(0.011)	(0.036)	(0.041)	(0.032)	(7.351)	(0.034)
Total	11.560	0.023	0.105	0.001	0.064	-0.000	0.020	93.524	0.004
	(16.845)	(0.051)	(0.061)	(0.011)	(0.071)	(0.063)	(0.035)	(8.319)	(0.031)

[a] **Note**: Sample averages by income level of the initial value of real GDP per capita in thousands of 2015 \$ (GDP_0), social protection expenditure as share of GDP \$ (SP_0) and food inflation FI_0. Δln(GDP), is the growth rates of real income. ΔFI and ΔSP are the absolute change of food inflation and social protection spending as a share of GDP. g^x is trade partners' growth. We use the World Bank definition of income groups. Standard errors are in parenthesis.

Table 4: Estimation results of main equation: PoU

	FD	FD-IV
y0	-0.019***	-0.016***
	(0.003)	(0.004)
Δ ln GDP pc	-0.045***	-0.107***
	(0.007)	(0.033)
Δ Food inflation	0.011**	0.063***
	(0.005)	(0.024)
constant	0.002***	0.003***
	(0.000)	(0.001)
N	2626	2011
Hansen test		5.1
p value		(0.16)

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Column 1 shows OLS results while column 2 has the corresponding IV estimates.

Table 5: First stages of main equation: PoU

	Δ ln GDP pc	Δ Food inflation
Global harvest shock (t-1)	0.000	-0.003***
	(0.000)	(0.001)
Trade partner growth	0.397***	0.164**
	(0.088)	(0.066)
Trade partner growth (t-1)	-0.079***	-0.010
	(0.026)	(0.057)
Δ ln CTOT	0.076*	0.122**
	(0.043)	(0.061)
Δ ln CTOT (t-1)	0.151***	-0.080
	(0.040)	(0.050)
y0	0.017	0.013**
	(0.015)	(0.005)
constant	0.011***	-0.005***
	(0.003)	(0.002)
N	2011	2011
F stat	8.7	11.8
p value	(0.000)	(0.000)

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Column 1 shows first stage estimates for GDP growth and column 2 for inflation changes.

Table 6: Estimation results of main equation: extended controls (1)

	FD	FD-IV	First stages
y0	-0.034***	-0.028***	
	(0.006)	(0.006)	
Δ ln GDP pc	-0.038***	-0.077**	18.5
	(0.009)	(0.031)	(0.000)
Δ Food inflation	0.005	0.035	4.7
	(0.007)	(0.030)	(0.000)
Δ Soc protection exp.	-0.001**	-0.003*	7.3
	(0.000)	(0.002)	(0.000)
constant	0.002***	0.003***	
	(0.000)	(0.001)	
N	1224	920	
Hansen test		6.9	
p value		(0.08)	

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Column 1 shows OLS results while column 2 has the corresponding IV estimates. The last column shows the F test statistics from the first stage of each regressor and the corresponding p value.

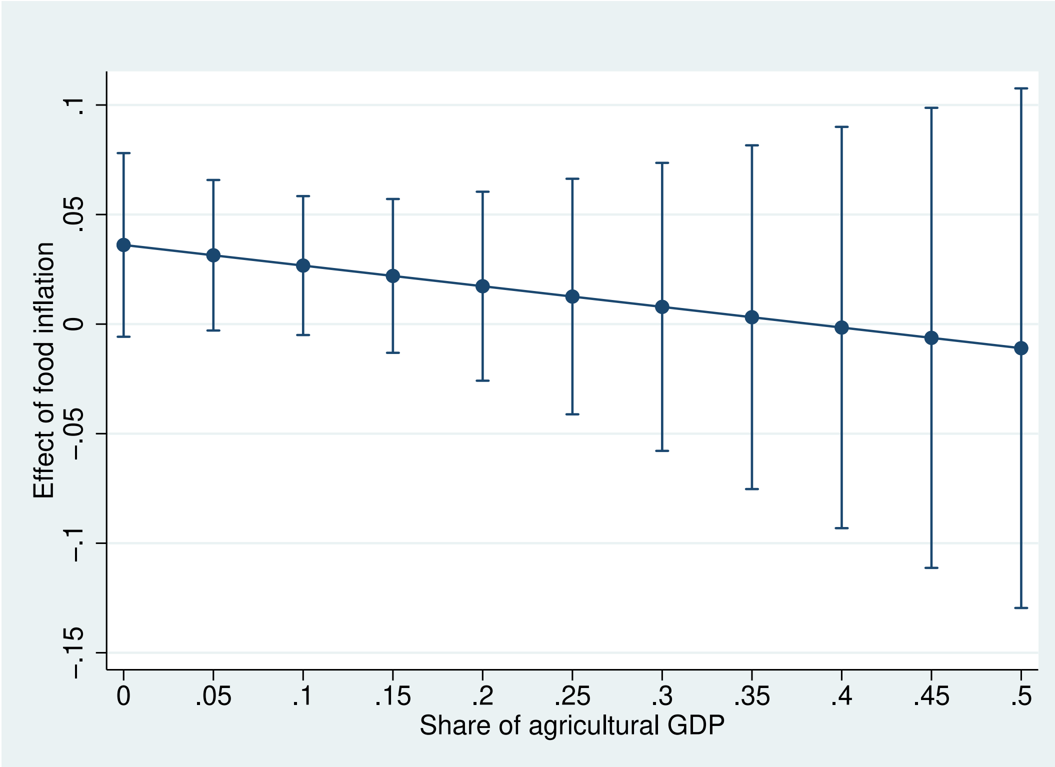

Figure 4: Food price effects variation for undernourishment.

Table 7: Food inflation effects heterogeneity: agricultural GDP

	FD-IV	First stages
Δ ln GDP pc	-0.081**	6.7
	(0.033)	(0.000)
Δ Food inflation	0.036*	4.9
	(0.021)	(0.000)
Agricultural GDP	0.023	2.4
	(0.015)	(0.000)
Δ Food inflation × Ag. GDP	-0.094	2.2
	(0.145)	(0.000)
y0	-0.036***	
	(0.013)	
constant	0.002**	
	(0.001)	
N	1487	
Hansen test	14.3	
p value	(0.57)	

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The first column shows IV estimates of equation 24. The last column show the F test statistics from the first stage of each regressor and its p value.

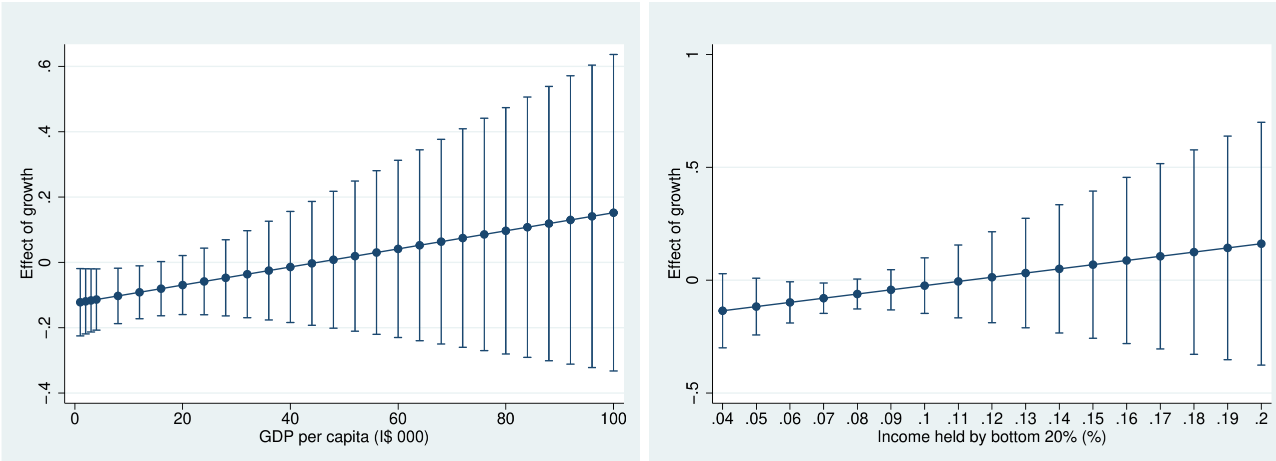

Figure 5: Growth effects variation for undernourishment.

Table 8: Interactions equation estimates: growth effects on PoU

	FD-IV	First stages
Δ ln GDP pc	-0.243	8.5
	(0.170)	(0.000)
Δ Food inflation	0.011	4.3
	(0.018)	(0.000)
GDP pc level	-0.000	8.5
	(0.000)	(0.000)
Income bottom 20%	-0.147	3.6
	(0.102)	(0.000)
Δ ln GDP pc × GDP pc level	0.003	4.9
	(0.003)	(0.000)
Δ ln GDP pc × Income bottom 20 %	1.857	7.6
	(2.187)	(0.000)
y0	-0.029***	
	(0.009)	
constant	0.014**	
	(0.007)	
N	1397	
Hansen test	12.9	
p value	(0.53)	

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The first column shows IV estimates of equation 24. The last column shows the F test statistics from the first stage of each regressor and its p value.

Table 9: Estimates with alternative set of instruments

	FD-IV
y0	-0.016***
	(0.004)
Δ ln GDP pc	-0.096***
	(0.035)
Δ Food inflation	0.043*
	(0.023)
constant	0.002***
	(0.001)
N	2011
Hansen test	4.9
p value	(0.17)

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10: First stage: alternative instruments

	Δ ln GDP pc	Δ Food inflation
Regional harvest shock (t-1)	-0.000**	-0.001***
	(0.000)	(0.000)
Trade partner growth	0.377***	0.177***
	(0.083)	(0.068)
Trade partner growth (t-1)	-0.070***	-0.028
	(0.025)	(0.055)
Δ ln CTOT	0.080*	0.129**
	(0.042)	(0.062)
Δ ln CTOT (t-1)	0.154***	-0.089*
	(0.040)	(0.048)
y0	0.018	0.012**
	(0.015)	(0.006)
constant	0.011***	-0.005***
	(0.003)	(0.002)
N	2011	2,011
F stat	16.5	12.4
p value	(0.000)	(0.000)

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: Sensitivity to controlling for wars

	FD	FD-IV	First stages
y0	-0.021***	-0.016***	
	(0.003)	(0.004)	
Δ ln GDP pc	-0.046***	-0.106***	8.5
	(0.007)	(0.033)	(0.000)
Δ Food inflation	0.010**	0.064***	11.8
	(0.005)	(0.024)	(0.000)
Armed conflict	0.002***	0.002	
	(0.001)	(0.001)	
constant	0.001***	0.002***	
	(0.000)	(0.001)	
N	2615	2011	
Hansen test		5.1	
p value		(0.17)	

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The last column shows the F test statistics from the first stage of each regressor and its p value.

Appendix B: Mathematical Proofs

Proof of Proposition 1.

(i) The food price derivatives of the threshold income levels associated with the PoU and POV are:

$$\frac{dy^{PoU}}{dp_F} = \frac{\left(\tilde{\alpha} + p_F \frac{d\tilde{\alpha}}{dp_F}\right) \underline{Q} - \kappa \frac{d\mu_y}{dp_F}}{1 - \kappa - p_F \underline{Q} \frac{d\tilde{\alpha}}{dy^{PoU}}} = \frac{\tilde{\alpha}\underline{Q}}{1-\kappa} \frac{1 + \frac{\eta - \epsilon_F}{\epsilon_F} \frac{\tilde{\alpha} - \lambda}{\tilde{\alpha}} \left(\xi_0 + \xi_1 \frac{p_F \underline{C_F}}{y^{d\star} - p_F \underline{C_F}}\right) - \kappa \frac{p_F (d\mu_y / dp_F)}{\tilde{\alpha} p_F \underline{Q}}}{1 + \frac{\eta - \epsilon_F}{\epsilon_F} \frac{\tilde{\alpha} - \lambda}{\tilde{\alpha}} \xi_1 \frac{\tilde{\alpha} p_F \underline{Q}}{y^{d\star} - p_F \underline{C_F}}} \tag{25}$$

$$\frac{dy^{POV}}{dp_F} = \frac{\frac{dP}{dp_F}\underline{R} + \underline{C_F} - \kappa \frac{d\mu_y}{dp_F}}{1 - \frac{1}{1-\kappa} \frac{dP}{dy^{POV}} \underline{R}} \tag{26}$$

with

$$\frac{d\tilde{\alpha}}{dy^{POV}} = \frac{d\tilde{\alpha}}{dy^{PoU}} = -\frac{\eta - \epsilon_F}{\epsilon_F} (\tilde{\alpha} - \lambda) \frac{1}{P} \frac{dP}{dy^{PoU}}, \tag{27}$$

$$\frac{\partial \tilde{\alpha}}{\partial (p_F/P)} = \frac{\eta - \epsilon_F}{\epsilon_F} (\tilde{\alpha} - \lambda) \frac{1}{p_F/P} \gtrless 0 \text{ if } \eta \gtrless \epsilon_F, \tag{28}$$

$$\frac{dP}{dy^{PoU}} = (1-\kappa) \frac{P}{y^{d\star} - p_F \underline{C_F}} \xi_1, \tag{29}$$

$$\frac{dP}{dp_F} = \frac{P}{p_F} \left[\frac{(1-\eta) m_F - [(\epsilon_F - 1) m_F + (\epsilon_{NF} - 1) m_{NF}] \frac{p_F \underline{C_F}}{y^{d\star} - p_F \underline{C_F}}}{(\epsilon_F - \eta) m_F + (\epsilon_{NF} - \eta) m_{NF}} \right], \tag{30}$$

$$\frac{d}{dp_F} \left(\frac{p_F}{P}\right) = \frac{1}{P} \left(\xi_0 + \xi_1 \frac{p_F \underline{C_F}}{y^{d\star} - p_F \underline{C_F}} \right), \tag{31}$$

and where

$$\xi_0 \equiv \left[\frac{(\epsilon_F - 1) m_F + (\epsilon_{NF} - \eta) m_{NF}}{(\epsilon_F - \eta) m_F + (\epsilon_{NF} - \eta) m_{NF}} \right], \tag{32}$$

$$\xi_1 \equiv \left[\frac{(\epsilon_F - 1) m_F + (\epsilon_{NF} - 1) m_{NF}}{(\epsilon_F - \eta) m_F + (\epsilon_{NF} - \eta) m_{NF}} \right], \tag{33}$$

$$m_F \equiv \alpha \left(\frac{y^d(h) - p_F \underline{C_F}}{P} \right)^{\epsilon_F - 1} \left(\frac{p_F}{P} \right)^{1-\eta}, \tag{34}$$

$$m_{NF} \equiv (1-\alpha)\left(\frac{y^d(h) - p_F\underline{\underline{C_F}}}{P}\right)^{\epsilon_F - 1}\left(\frac{p_{NF}}{P}\right)^{1-\eta}, \tag{35}$$

and $\frac{d\mu_y}{dp_F}$ is either 0 (urban economy) or R_F (rural economy) (see Assumption 3). Without further assumptions, one cannot sign the derivative $\frac{dy^{PoU}}{dp_F}$ which can be positive or negative. That $\frac{\partial F}{\partial \mu_y}\frac{d\mu_y}{dp_F}$ is either zero or negative follows from the fact that $\frac{d\mu_y}{dp_F}$ is either zero (urban case) or positive (rural case), while $\frac{\partial F}{\partial \mu_y}$ is strictly negative based on Assumption 1. This completes the proof for (i).

(ii)-(iii) The results follow directly from inspecting the expressions for the semi elasticities $\frac{dPoU}{d\mu_y/\mu_y}$ and $\frac{dPoU}{d\kappa/\kappa}$ and applying Assumption 1.

Proof of Proposition 2.

(i)-(iv) The income and price semi-elasticities based on eqs. (17)-(20) read:

$$\frac{dPoU_U}{dR/R} = -\frac{1}{\rho}PoU < 0$$

$$\frac{dPoU_U}{dp_F/p_F} = \frac{\tilde{\alpha} + (\eta-1)(\tilde{\alpha}-\lambda)m_{NF}}{\tilde{\alpha}}\frac{1}{\rho}PoU_U > 0$$

$$\frac{dPoU_R}{dR_F/R_F} = -\frac{1}{\rho}PoU < 0$$

$$\frac{dPoU_R}{dp_F/p_F} = \frac{(\eta-1)(\tilde{\alpha}-\lambda)m_{NF}}{\tilde{\alpha}}\frac{1}{\rho}PoU_R \gtreqless 0 \Longleftrightarrow \eta \gtreqless 1$$

$$\frac{dPOV_U}{dR/R} = -\frac{1}{\rho}POV_U < 0$$

$$\frac{dPOV_U}{dp_F/p_F} = \frac{m_{NF}\frac{p_F}{P}\lambda\underline{\underline{Q}}}{\underline{R} + \frac{p_F}{P}\lambda\underline{Q}}\frac{1}{\rho}POV_U > 0$$

$$\frac{dPOV_R}{dR_F/R_F} = -\frac{1}{\rho}POV_R < 0$$

$$\frac{dPOV_R}{dp_F/p_F} = -\frac{m_{NF}\frac{P}{p_F}\underline{R}}{\frac{P}{p_F}\underline{R} + \lambda\underline{Q}}\frac{1}{\rho}POV_R < 0$$

The results then follow from inspecting the signs of these semi elasticities (for $\eta \gtrless 1$) and, where applicable, comparing the magnitudes of these derivatives. This completes the proof.

Proof of Proposition 3.

(i) Differentiating the PoU (i.e., $F(y;\mu,\sigma)$) with respect to σ, and rearranging, we obtain the following semi elasticity:

$$\frac{dPoU}{d\sigma/\sigma} = -\left(\frac{ln(y^{PoU}) - \mu}{\sigma}\right)\Phi'\left(\frac{ln(y^{PoU}) - \mu}{\sigma}\right). \tag{36}$$

Since $\Phi'(\cdot) > 0$ we have $\frac{dPoU}{d\sigma/\sigma} \gtrless 0$ iff $y^{PoU} \lesseqgtr e^{\mu}$.

(ii) Differentiating the PoU (i.e., $F(y;\mu,\rho)$) with respect to ρ, and rearranging, we obtain the following semi elasticity:

$$\frac{dPoU}{d\rho/\rho} = -\left(\frac{1}{1+\rho} + ln(PoU)\right)PoU \tag{37}$$

It follows that $\frac{dPoU}{d\rho/\rho} \gtrless 0$ for $PoU \lesseqgtr e^{-\frac{1}{1+\rho}} \equiv \overline{PoU}$. This completes the proof.

Proof of Proposition 4.

Let us define $s_q \equiv \frac{p_F\underline{Q}}{\mu_y}$. Then note that the semi income elasticity in this case can be written as:

$$\frac{dPoU}{d\mu_y/\mu_y} = -\frac{1}{\rho}\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa}PoU < 0 \tag{38}$$

Differentiating the semi income elasticity $\frac{dPoU}{d\mu_y/\mu_y}$ with respect to μ_y and ρ respectively, gives:

$$\begin{aligned}\frac{d}{d\mu_y}\left(\frac{dPoU}{d\mu_y/\mu_y}\right) = \frac{dPoU}{d\mu_y}\left(\frac{dPoU/PoU}{d\mu_y/\mu_y} + \frac{\kappa}{1-\kappa}\frac{\mu_y}{y^{PoU}}\right) \gtrless 0 \\ \Leftrightarrow \frac{\kappa}{1-\kappa}\frac{\mu_y}{y^{PoU}} \lesseqgtr -\frac{dPoU/PoU}{d\mu_y/\mu_y} = \frac{1}{\rho}\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa} \\ \Leftrightarrow \rho\kappa \lesseqgtr \tilde{\alpha}s_q\end{aligned} \tag{39}$$

and

$$\begin{aligned}\frac{d}{d\rho}\left(\frac{dPoU}{d\mu_y/\mu_y}\right) &= -\frac{1}{\rho}\frac{dPoU}{d\mu_y/\mu_y} - \frac{1}{\rho}\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q-\kappa}\frac{dPoU}{d\rho} \\ &= -\left(\frac{dPoU/PoU}{d\mu_y/\mu_y}\right)\left[1+\frac{1}{1+\rho}+ln\left(PoU\right)\right]\frac{PoU}{\rho} \\ = -\left(\frac{dPoU/PoU}{d\mu_y/\mu_y}\right)\left[1+ln\left(\frac{PoU}{\overline{\overline{PoU}}}\right)\right]\frac{PoU}{\rho} &\gtrless 0 \Leftrightarrow PoU \gtrless e^{-\frac{2+\rho}{1+\rho}}\end{aligned} \tag{40}$$

where the last step in equation (39) follows from $\frac{\kappa}{1-\kappa}\frac{\mu_y}{y^{PoU}} = \frac{\kappa}{\tilde{\alpha}s_q-\kappa}$. This completes the proof.

Derivatives for model calibration with isoelastic non-homothetic CES preferences

Let $\phi(x) \equiv \frac{1}{\sigma\sqrt{2\pi}}e^{-x^2/2}$ and $\Phi(x) \equiv \int_{-\infty}^{x} e^{-t^2/2}dt$ represent the PDF and the CDF of the standard normal distribution. Then the lognormal CDF's for the urban and rural economy respectively are:

$$F_U = \Phi\left(\frac{ln\left(y^{PoU}\right)-\mu}{\sigma}\right) = \Phi\left(\frac{ln\left(\frac{y^{PoU}}{\mu_y}\right)+\sigma^2/2}{\sigma}\right) \tag{41}$$

and

$$F_R = \Phi\left(\frac{ln\left(y_R^{PoU}\right)-\mu}{\sigma}\right) = \Phi\left(\frac{ln\left(\frac{y_R^{PoU}}{\mu_y}\right)+\sigma^2/2}{\sigma}\right) \tag{42}$$

where

$$\frac{y^{PoU}}{\mu_y} = \frac{\tilde{\alpha}p_F\underline{Q}-\kappa\mu_y}{(1-\kappa)\mu_y} \tag{43}$$

$$\frac{y_R^{PoU}}{\mu_y} = \frac{\tilde{\alpha}\underline{Q}-\kappa R_F}{(1-\kappa)R_F} \tag{44}$$

Assuming $\lambda = 0$ (i.e., standard isoelastic preferences) and a log-normal income distribution, the food price and income elasticities are:

$$\frac{dF_U}{d\mu_y/\mu_y} = -\phi(\cdot)\left(1+\frac{\kappa}{1-\kappa}\frac{\mu_y}{y^{PoU}}\right) = -\phi(\cdot)\left(\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q-\kappa}\right) \tag{45}$$

$$\frac{dF_R}{dR_F/R_F} = -\phi(\cdot)\left(1 + \frac{\kappa}{1-\kappa}\frac{\mu_y}{y^{PoU}}\right) = -\phi(\cdot)\left(\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa}\right) \tag{46}$$

$$\frac{dF_U}{dp_F/p_F} = \phi(\cdot)\frac{1}{y^{PoU}}\frac{dy^{PoU}}{dp_F/p_F} = \phi(\cdot)\left(\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa}\right)\left(\frac{1 + \frac{\eta-\epsilon_F}{\epsilon_F}\xi_0}{1 + \frac{\eta-\epsilon_F}{\epsilon_F}\xi_1}\right) \tag{47}$$

$$\frac{dF_R}{dp_F/p_F} = \phi(\cdot)\frac{1}{y^{PoU}}\frac{dy_R^{PoU}}{dp_F/p_F} - \phi(\cdot)\frac{1}{\mu_y}\frac{d\mu_y}{dp_F/p_F} = \phi(\cdot)\left(\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa} - \frac{\xi_1}{\xi_0}\right)\left(\frac{\frac{\eta-\epsilon_F}{\epsilon_F}\xi_0}{1 + \frac{\eta-\epsilon_F}{\epsilon_F}\xi_1}\right) \tag{48}$$

where

$$s_q \equiv \frac{p_F \underline{Q}}{\mu_y}. \tag{49}$$

In case the income distribution is Pareto (our Example 2), the log-normal PDF $\phi(\cdot)$ is replaced with $\frac{1}{\rho}PoU$, e.g.,

$$\frac{dF_U}{d\mu_y/\mu_y} = -\frac{1}{\rho}PoU_U\left(\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa}\right) \tag{50}$$

$$\frac{dF_U}{dp_F/p_F} = \frac{1}{\rho}PoU_U\left(\frac{\tilde{\alpha}s_q}{\tilde{\alpha}s_q - \kappa}\right)\left(\frac{1 + \frac{\eta-\epsilon_F}{\epsilon_F}\xi_0}{1 + \frac{\eta-\epsilon_F}{\epsilon_F}\xi_1}\right). \tag{51}$$

Supplementary Online Appendix not for publication

Instrument construction

Our first external instrument, the change in the commodities terms of trade, is defined as in Gruss and Kebhaj (2021):

$$\Delta ln(CTOT_{i,t}) = \sum_j \Delta ln\left(P_{j,t}\right)\Omega_{i,j,t} \tag{52}$$

where $P_{j,t}$ is the price of the j-th commodity at time t and the annual weight of each commodity in country i is given by the share of net exports in output:

$$\Omega_{i,j,t} = \frac{1}{3}\sum_{s=1}^{3}\frac{x_{i,j,t-s} - m_{i,j,t-s}}{GDP_{i,t-s}} \tag{53}$$

Here, $x_{i,j,t}$ ($m_{i,j,t}$) denotes the exports (imports) value of commodity j of country i in year t. Our second external instrument, the export weighted-average growth rate of all N trading partners of country i, was inspired by Acemoglu et al. (2008), and is here calculated using three-year moving averages, that is,

$$g^x_{i,t} = \frac{\sum_{\tau=1}^{3} Xtot_{i,t-\tau}}{\sum_{\tau=1}^{3} GDP_{i,t-\tau}}\left(\sum_{j=1}^{j=N}\Omega_{i,j,t}g_{j,t}\right), \tag{54}$$

where

$$\Omega_{i,j,t} = \frac{\sum_{\tau=1}^{3} X_{i,j,t-\tau}}{\sum_{\tau=1}^{3} Xtot_{i,t-\tau}}, \tag{55}$$

and $g_{j,t}$ is the GDP growth rate of partner j in year t, and $X_{i,j,t}$ and $Xtot_{i,t}$ refers to goods exports from i to j and total goods exports by country i respectively.

Our third set of instruments constitutes of harvest shocks, the construction of which is inspired by Roberts and Schlenker (2013) and De Winne and Peersman (2021). We start by collecting production data (in million tons) for wheat, maize, soybeans and rice for all countries in the world from FAO (2023). Using measures of caloric content by crop suggested by Roberts and Schlenker (2013), we then construct total food supply (in kcal) as the sum of production of the 4 major staple foods (maize, rice, soybeans and wheat). We then apply a Hodrick-Prescott filter to separate, for each country, the production series into a cyclical component and a trend component, with the smoothing parameter set to 6.25 following

Ravn and Uhlig (2002). We take the cyclical component and interpret it as a proxy for weather induced yield fluctuations. Next, to construct the regional harvest shock series for country i, we sum the shocks of all countries in the country's region (excluding the shock of country i) and express it in per capita terms. Finally, the deviation from per capita trend production is then divided by the per capita trend to express the shock in percentage terms. The rest-of-world shock for country i is constructed similarly, except that the shocks are summed over all countries in the world except those countries in country's i own region.

Results for qualitative food insecurity indicators

In this section we presents the results for our two qualitative indicators of food insecurity, namely protein consumption and the energy share of staple foods.

Figure A1 shows that as countries develop, they tend to substitute cereals and staple foods with animal products. Both schedules show that substitution is fast at the beginning and slows down as countries move up the income ladder.

Moving to the regression analysis of the qualitative aspects of food insecurity, table A1 has the effects of the same set of regressors as before on our two diet composition variables. The first two columns report the FD estimates for the dietary energy share from starchy staples and average animal protein supply. Only income plays a role in dietary habits with a 1 pp increase in GDP per capita growth leading to a 0.049 pp reduction in cereals, roots and tubers consumption and 0.092 gr/cap/day increase in the consumption of animal products. In relative terms, the impact of income growth on animal protein consumption is three times larger than that on staples (0.29 vs 0.11 percent). Coefficients for food inflation are indistinguishable from zero. The effect of the initial conditions are negative and significant only for starchy staples consumption but small in size, indicating slow convergence of diet patterns across countries.

The last two columns of table A1 report FD-IV results. Coefficient estimates of income growth on starchy staples and animal protein consumption are significant and 1.5 times larger than the corresponding FD estimates. Salois et al. (2012) find a GDP elasticity of average protein consumption that is close to our FD estimate. We interpret this as an indication of the convenience of our choice to explicitly address endogeneity concerns, since

Salois, Tiffin, and Balcombe (2012) warn that the main caveat of their study is possible endogeneity bias. We note that the integration of animal products into diet occurs at a higher pace than the phasing out of cereals, roots and tubers, which are staples regardless of a country's level of development. As a result, their weight in diet reduces slowly, as higher income allows access to more expensive sources of calories and poor countries move towards richer and more balanced diets.

We notice that the FD-IV estimate of the effect of a rise in food inflation is small and insignificant for cereals consumption. For meat and fish consumption the effect is sizable and seems to indicate lower protein consumption as food inflation rises, although statistical precision is low. This is in line with our priors, since, demand for necessities like staples should be less price-responsive than the demand for higher-value foods. Further, diet composition, like the PoU, is more responsive to changes in real income than in food inflation. The reactivity of dietary habits to the business cycle shows that to avoid falling below the undernourishment threshold, people will use diet composition as a buffer to absorb income (and price) shocks.

Table A2 shows first stage estimation results for each endogenous variable in the two diet composition equations. Instruments have the expected sign and significance and F statistics confirm a strong relationship.[23] The Hansen test of overidentifying restrictions strongly supports instrument validity for both regressions (table A1).

The effect of growth on diet composition varies with the level of development and the overall level of inclusiveness of the economy. Results are represented graphically in figure A2, while the underlying FD-IV estimates of equation 24 are reported in table A3. The first stage is strong, but the test of overidentifying restrictions does not fully support the null hypothesis of exogeneity for the cereal equation. The top left graph in figure A2 shows that income growth leads to a strong reduction in the energy share of cereals, tubers and roots at the early stages of development. Consumption of animal-based food (top right graph) responds positively to growth and does not wane off until countries are quite far in their development process. In fact, meat and fish saturation of diets occurs at a level of GDP per capita of around USD 22 thousand, where staple consumption also stops decreasing. The bottom two graphs show how the growth elasticity of diet composition varies with the share of income held by the bottom

[23] They are almost identical since for both outcomes the same right hand side variables are included - with the exception of initial conditions - and the same instruments are used.

20 percent. In more unequal societies, the effects of growth induce stronger diet changes. This probably reflects the fact that more people are closer to the threshold in a more unequal economy, and the stronger changes in diet composition allow for more muted variations of caloric insufficiency.

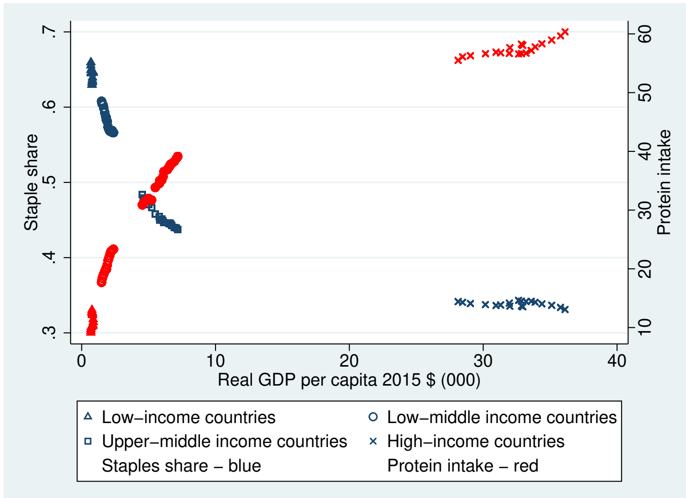

Figure A1: (C) Relationship between diet composition and GDP per capita by income group.

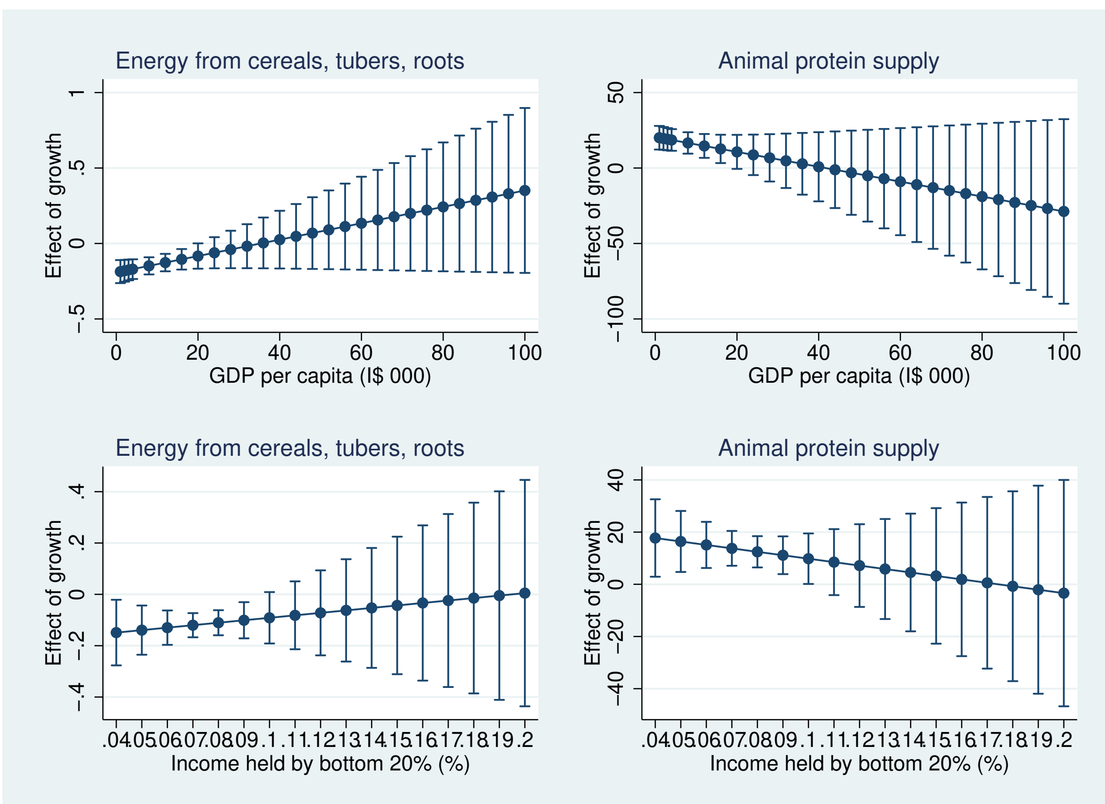

Figure A2: Growth effects variation for diet composition.

Table A1: Estimation results of main equation: diet composition

	FD		FD-IV	
	CER	PROT	CER	PROT
y0	-0.006***	-0.001	-0.005**	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Δ ln GDP pc	-0.049***	9.232***	-0.068*	14.257***
	(0.008)	(1.439)	(0.038)	(4.033)
Δ Food inflation	-0.001	-0.987	0.008	-5.334
	(0.004)	(1.122)	(0.029)	(3.813)
constant	0.003***	0.151**	0.003***	-0.035
	(0.001)	(0.063)	(0.001)	(0.142)
N	2318	2324	1781	1783
Hansen test			4.48	0.86
p value			(0.21)	(0.83)

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The first two columns show OLS results, while the last two columns have the corresponding IV estimates.

Table A2: First stage of main equation: diet composition

	CER		PROT	
	Δ ln GDP pc	Δ Food inflation	Δ ln GDP pc	Δ Food inflation
Global harvest shock (t-1)	-0.001*	-0.003***	-0.001*	-0.003***
	(0.000)	(0.001)	(0.000)	(0.001)
Trade partner growth	0.273***	0.180**	0.279***	0.179**
	(0.077)	(0.073)	(0.077)	(0.072)
Trade partner growth (t-1)	-0.054**	-0.013	-0.050**	-0.013
	(0.023)	(0.060)	(0.022)	(0.060)
Δ ln CTOT	0.082**	0.146**	0.080*	0.146**
	(0.041)	(0.074)	(0.041)	(0.074)
Δ ln CTOT (t-1)	0.111***	-0.080	0.109***	-0.080
	(0.040)	(0.056)	(0.040)	(0.057)
y0	0.049***	0.000	-0.000***	-0.000
	(0.010)	(0.004)	(0.000)	(0.000)
constant	-0.006	-0.005*	0.028***	-0.004**
	(0.005)	(0.002)	(0.003)	(0.002)
Observations	1781	1781	1,783	1,783
F stat	7.45	9.16	7.46	9.17
p value	(0.000)	(0.000)	(0.000)	(0.000)

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The first two columns show the first stage estimates of GDP growth and inflation changes for the equation of share of energy from staples. The last two columns show the same first stage estimates for the protein supply equation.

Table A3: Interactions equation estimates: growth effects on diet composition

	FD-IV		First stages	
	CER	PROT	CER	PROT
Δ ln GDP pc	-0.253*	28.972**	10.4	12.4
	(0.131)	(13.809)	(0.000)	(0.000)
Δ Food inflation	0.033	-3.496	4.9	4.9
	(0.022)	(2.875)	(0.000)	(0.000)
GDP pc level	0.000	-0.005	13.1	4.3
	(0.000)	(0.011)	(0.000)	(0.000)
Income bottom 20%	-0.108*	5.796	25	18.4
	(0.061)	(6.151)	(0.000)	(0.000)
Δ ln GDP pc $\times$ GDP pc level	0.005*	-0.493	7.7	4.9
	(0.003)	(0.331)	(0.000)	(0.000)
Δ ln GDP pc $\times$ Income bottom 20 %	0.962	-132.006	11.4	13.8
	(1.781)	(180.298)	(0.000)	(0.000)
y0	0.002	0.003		
	(0.007)	(0.008)		
constant	0.008*	-0.539		
	(0.004)	(0.362)		
N	1375	1377		
Hansen test	29	28		
p value	(0.00)	(0.01)		

[a] **Note**: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The first two columns show IV estimates of equation 24. The last columns show the F test statistics from the first stage of each regressor and its p value.

PUBLICATIONS

How do Economic Growth and Food Inflation Affect Food Insecurity?

Working Paper No. WP/2024/188