Agricultural (Dis)Incentives and Food Security: Is There a Link?

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Using the World Bank database "Distortions to agricultural incentives," this paper analyzes the impact that agricultural (dis)incentives have on food security for a wide sample of countries over the 1990–2010 period. We adopt a continuous treatment approach applying generalized propensity score matching to reduce potential biases stemming from differences in observed country characteristics. The results provide strong evidence of self-selection and heterogeneous food security impacts at different levels of policy intensity. Estimates of the dose-response functions show that both discrimination against agriculture and large support for it lead to poor performance in the availability, access, and utilization dimensions of food security.

Key words: Agricultural (dis)incentives, cross-country analysis, food security, generalized propensity score, impact evaluation.

JEL codes: C21, F14, F60, O50, Q17.

Traditionally, the agricultural sector has been subject to heavy-handed government interventions. In recent years many developing countries have reduced their anti-agriculture and anti-trade biases, and high-income countries have eliminated some of the most distortive policies such as export subsidies. Nevertheless, existing agricultural and trade policies still account for an estimated 70% of the global welfare cost of all merchandise trade distortions despite the agricultural sector accounting for only 6% of global trade and 3% of global GDP (Anderson, Cockburn, and Martin 2010).

The debate on the consequences of these government interventions on food security (FS) is receiving particular attention from policy makers and academics ranging from those who argue that public intervention softens hunger, to those who believe that complete market liberalization is the best approach to achieving FS. There is also a lack of consensus on the empirical relationship between agricultural (dis)incentives and potential gains or losses in terms of FS (Food and Agriculture Organization of The United Nations 2015).[1] The main reasons for this are the difficulties involved in measuring the intensity of government interventions and the level of FS, the choice of an adequate methodology to assess the policy impact, and the multiplicity of the channels through which public support for agriculture affects the dimensions of FS, that is, availability, access, utilization,

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[1] McCorriston et al. (2013) review the empirical evidence on the links between agricultural trade liberalization and FS in developing countries. Thirteen of thirty-four cases predicted that FS would improve, ten predicted a decline, while the remaining eleven reported a mixed outcome, with FS metrics varying across population segments, regions, and time, or with alternative FS metrics indicating different outcomes for specific countries.

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and stability (Diaz-Bonilla and Ron 2010; Díaz-Bonilla 2015; Laroche-Dupraz and Huchet-Bourdon 2016). Agricultural policies can have a direct effect on domestic food availability through their impact on factor, input, and product markets, which allows them to contribute to determining the levels and geographical and temporal distribution of production, storage, and processing. Policies can influence access to food by affecting producers' profits and consumers' expenditure, as well as food utilization through the promotion of production diversification and new dietary habits. Policies can also have an effect on the stability of FS since income and commodity price uncertainties make producers either under-invest or invest in the "wrong projects" (Bertola and Caballero 1994), and make consumers deviate from a smooth consumption path (Montalbano 2011). Finally, policy interventions can affect national budgets, contributing to (or threatening) the funding of other domestic policies such as national investment in health and education, which directly or indirectly promote increased FS.

The large scale of the problem means that the net effect of policies on the various FS dimensions cannot be determined a priori but has to be investigated empirically and must take into consideration the different underlying factors influencing both the level of government intervention and FS performance at the country level. The starting point is that policy interventions are not random; they are driven by a series of macro-economic factors such as the country's level of development, agro-climatic conditions, and natural endowments, among other characteristics (Yu, You, and Fan 2010; Matthews 2013). Since these factors are also associated with FS performance, there are several possible sources of endogeneity that could bias the empirical analysis.

In what follows, we treat self-selection bias by relying on a generalization of the binary propensity score matching—that is, generalized propensity score (GPS)—as originally proposed by Hirano and Imbens (2004) and Imai and van Dyk (2004). Unlike other matching techniques, GPS allows continuous treatment, which is particularly appropriate in this framework since agricultural policy intensity varies widely from country to country, and over time.[2] Going beyond the evidence provided by single-country case studies, our empirical analysis includes a sample of sixty-four countries over the 1990–2010 time period. To this end, we use World Bank data from the "Distortions to agricultural incentives" database (Anderson and Nelgen 2012b), which provides indicators, such as the nominal rate of assistance, that convert different policy instruments into a common metric for a large set of countries.

Our study contributes to the literature in three ways. First, it represents an initial attempt to perform a rigorous quantitative analysis of the impact of national agricultural policies on FS at the aggregate level. Second, it provides a comprehensive analysis in terms of both geographical coverage and time length. Third, it confirms the presence of self-selection bias in the causal aggregate relationship between agricultural incentives and the four dimensions of FS.

Our results show that: (*a*) agricultural incentives matter, and have heterogeneous impacts on the four dimensions of FS; (*b*) primary sector taxation has a consistent negative impact on all FS dimensions, while moderate support tends to have positive effects on three (i.e., availability, access, and utilization) of the four dimensions studied; and (*c*) excessive support for the agricultural sector could be as damaging as taxation.

These results have numerous policy implications. First, there is no one-size-fits-all solution since the impacts of agricultural policies are differentiated across FS dimensions. Second, the strategy pursued by several developing country governments of taxing agricultural producers to make additional resources available for (supposedly) more dynamic sectors turns out to have a negative impact on FS. This is probably due to the costs involved in transferring resources across sectors (Anderson and Masters 2009). Third, the positive impact of supporting agricultural producers comes at a cost that eventually counterbalances the initial benefits. This is particularly relevant to those poor countries—especially in Sub-Saharan Africa—that are

[2] GPS matching has been applied to impact evaluation problems lacking experimental conditions such as the impact of labor market programs (Kluve 2010; Kluve et al. 2012), regional transfer schemes (Becker, Egger, and von Ehrlich 2012), foreign direct investments (Du and Girma 2009) and European Union (EU) preferential margins (Magrini, Montalbano, and Nenci 2017), as well as assessments of the relationship between migration and trade (Egger, von Ehrlich, and Nelson 2012), and the impact of improved maize technologies on smallholders' welfare (Kassie, Jaleta, and Mattei 2014).

addressing the recent food price crises with extremely costly (over $1 billion annually in Africa alone) and frequently ineffective policy interventions to protect domestic producers (Jayne 2012; Benson et al. 2013; Torero 2016). While our analysis clearly shows that agricultural (dis)incentives are effective at influencing FS, it does not provide normative implications regarding the utilization of several policy instruments, and does not consider the costs and benefits of specific policy interventions. However, it suggests the need for further analyses of the actual country-level policy mix corresponding to different levels of agricultural sector support.

Methodological Approach

A number of different empirical methods have been applied to examine the links between agricultural policy and FS (Adebua, Okurut, and Odowee 2002; Pyakuryal, Roy, and Thapa 2010; Yu, You, and Fan 2010; Matthews 2013; Laroche-Dupraz and Huchet-Bourdon 2016). To the best of our knowledge, there are no investigations into the causal relationship between policy interventions and FS using non-parametric methods. We redress this imbalance by using a non-parametric method that allows us to control for possible sources of self-selection without the need to impose specific constraints on the relationship between agricultural incentives and FS. We use matching econometrics, namely GPS, because this technique does not require separability of outcomes, choice equations, and exclusion restrictions, or the adoption of specific functional forms of outcome equations (Heckman and Navarro-Lozano 2004; Imbens and Wooldridge 2009). Since FS is a multi-dimensional phenomenon and its relationship with agricultural policies lacks a robust theoretical model framework, the choice of a non-parametric approach seems to be the most appropriate.[3]

Our methodological choice involves some major issues. The first is that agricultural (dis) incentives should be associated with an *ex ante* target, that is, an outcome variable against which the treatment impact can be properly evaluated. In this respect, whether and how FS can be clearly expressed using macro variables is questionable. This issue has been debated at length by international organizations and policy makers in search of aggregate FS indicators, and by the relevant academic literature on the development of an aggregate conceptual framework to analyze the interactions between policies and FS outcomes: here, we rely on the most commonly-used macro-level FS measures (Smith 1998; Diaz-Bonilla, Thomas, and Robinson 2002; Diaz-Bonilla and Ron 2010; Laroche-Dupraz and Huchet-Bourdon 2016).

A second issue is that the treatment must be clearly identified and must be observable. In this respect, the World Bank "Distortions to agricultural incentives" database has greatly increased the clarity and identifiability of the treatment associated with the agricultural policies. Many and various pairs of instruments have been synthesized to produce a single standardized measure, that is, nominal rate of assistance. Furthermore, unlike evaluation exercises based on binary treatment, the agricultural incentive intensity is a continuous variable. In our study, the units of observation are treated with different intensities, and the final effect depends more on that intensity than only on being treated or not. Below we show how the multivalue nature of the treatment represents an opportunity rather than a limitation to identify and estimate the impact of policies on FS.

The third and most important issue relates to a major limitation of the chosen approach, which might prevent its application in this context. In matching exercises with binary treatment, it is necessary to have a proper control group. This means that there are counterfactual observations where the outcome variable is observed without being subjected to the treatment. However, in the case of agricultural incentives, finding a proper strategy to identify counterfactuals and compare them to treated units can be tough if not impossible because it is difficult to identify non-treated units (i.e., countries not adopting agricultural policies). Although it would be possible to observe a non-treated sample, this could hardly be considered a proper counterfactual sample because the decision would likely be driven by unobserved factors that affect both treatment assignment and outcome. In other words, the specificity of agricultural (dis)incentives as a treatment renders it almost impossible to get rid of the selection-on-

[3] Parametric techniques would imply an imposition of restrictions (e.g., linearity and normal distribution of the error term) on the treatment-outcome relationship. If this relationship is not supported by the theory, the estimates will be based on strong and (probably wrong) assumptions.

(un)observables bias in a treated versus non-treated framework (Esposti 2014).

In such a difficult and unconventional condition (multiple outcomes, multiple and multi-value treatments, no natural counterfactuals), GPS provides several advantages. First, it allows the use of matching techniques even if the treatment is a continuous variable such as a measure of agricultural incentives. Second, it allows control for endogeneity bias due to the fact that agricultural incentives are not randomly assigned but are likely to be endogenously correlated with macro-economic factors and government objectives. Third, GPS helps us to isolate the impact of agricultural policies from other observable confounding events and to control for the presence of non-linearities in the relationship between the policy and the FS outcome. Fourth, it does not require non-treated observations because it creates internal control groups for the various levels of the continuous treatment.

The GPS Estimator

Generalized propensity score is a non-parametric method that corrects for selection bias in settings with continuous treatment by comparing units that are similar in their observable determinants of "treatment intensity." The basic setup of the GPS method described below is based on Hirano and Imbens (2004) and Imai and van Dyk (2004). We use index $i = 1, \ldots, N$ to refer to a random sample of units. The GPS method is based on the following assumptions: for each i we postulate the existence of a set of potential outcomes, $Y_i(t)$, for $t \in \Gamma$, where Γ is a continuous set of potential treatment values.[4] Hirano and Imbens (2004) refer to $Y_i(t)$ for $t \in \Gamma$ as the *unit-level* dose-response function (DRF). We are interested in estimating the *average* DRF, $D(t)$, across all units i, which illustrates the expected value of the outcome variable conditional on continuous treatment as follows:

$$(1) \quad D(t) = E[Y_i(t)].$$

Estimation of the $D(t)$ uses information on three sets of data: a vector of covariates, $\boldsymbol{X}_i$, the treatment received, T_i, and the potential outcome corresponding to the level of the treatment received, $Y_i = Y_i(T_i)$. Following Hirano and Imbens (2004), we assume the following: $Y_i(t)_{t\in\Gamma}$, T_i, and $\boldsymbol{X}_i$ are defined on a common probability space; T_i is continuously distributed with respect to a Lebesgue measure on Γ; and $Y_i = Y_i(T_i)$ is a well-defined random variable. To simplify the notation, we will drop the i subscript in the sequel.

Let $r(t, \boldsymbol{x})$ be the conditional density of the treatment given the covariates

$$(2) \quad r(t,x) = f_{T|X}(t|x)$$

then the GPS is

$$(3) \quad R = r(T,X).$$

Generalized propensity score removes the bias associated with differences in covariates in three steps. In the first step, GPS is estimated, and its balancing property is checked. Using a normal distribution for the treatment given the covariates

$$(4) \quad T|X \sim N(\beta_0 + \beta_1' X, \sigma^2)$$

we estimate the parameters $\hat{\beta}_0$, $\hat{\beta}_1$, and $\hat{\sigma}^2$ by maximum likelihood. Hence, the estimated GPS is

$$(5) \quad \hat{R} = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[-\frac{1}{2\hat{\sigma}^2}(T - \hat{\beta}_0 - \hat{\beta}_1' X)^2\right].$$

If balancing holds, observations within GPS strata can be considered as identical in terms of their observable characteristics, independent of their actual level of treatment.[5]

Two additional steps are needed to eliminate the bias associated with differences in the covariates. The first one is estimating the conditional expectation of the outcome as a function of two scalar, T and R, as follows:

$$(6) \quad \beta(t,r) = E[Y|T = t, R = r] = \psi[t,r;\alpha]$$

where α are the parameters to be estimated. This is generally assumed to be a flexible parametric specification between the three variables at different orders of the polynomial terms. The statistical significance of the GPS parameters is a sign that selection bias is an issue. Interaction terms between the treatment level and the GPS

[4] Here, Γ is an interval $[t_0, t_1]$.

[5] Note that as long as sufficient covariate balance is achieved, the exact procedure for estimating GPS is of secondary importance (Kluve et al. 2012).

are introduced to control for the marginal impact of the treatment relative to the GPS.

The second step involves estimating the average DRF of the outcome by averaging the conditional expectation over the GPS at any different level of treatment, as follows:

$$(7) \quad D(t) = E[\beta(t, r(t, X))].$$

Furthermore, we can calculate the varying marginal effects of the treatment by estimating the treatment effect function (TEF) that corresponds to the first derivative of the DRF, as follows:

$$(8) \quad \theta(D) = D(t + \delta) - D(t).$$

The main purpose in estimating the GPS is to create covariate balancing. However, the validity of R as a measure of similarity or dissimilarity across observations depends crucially on the validity of a set of standard assumptions in the impact evaluation literature. The most important one is "weak unconfoundedness." which implies that conditional on observable characteristics, the treatment can be considered random.[6] In other words, for observations in the strata with the same value of $r(t, \boldsymbol{X})$, the GPS has the following property:

$$(9) \quad X \perp 1\{T = t\} | r(t, X).$$

This assumption, combined with "the balancing property," guarantees that the treatment assignment is weakly unconfounded given the GPS. The assumption of "weak unconfoundedness" potentially could be violated in the case of endogeneity. In our analysis, the main risk of endogeneity arises from the possibility of reverse causality between the agricultural (dis)incentives and FS caused by unobserved factors that influence both treatment and outcomes. To address this, we test for endogeneity using Instrumental Variables (IV) and a falsification test. In particular, we use the Hausman test to verify whether the treatment coefficient in a Fixed Effects (FE) model is statistically different from the coefficient in a IV-FE model with the instrumented treatment. For the falsification test, we control for feedback effects in the FE model to test whether future values of the treatment influence current values of the outcome.

The validity of both weak unconfoundedness and the balancing property is coupled with the stable unit treatment value assumption (SUTVA). The SUTVA is comprised of two parts: the "unique treatment assumption," that is, the treatment is identical for each treated observation; and the "non-interference assumption," that is, treatment applied to one unit does not affect the outcome of another unit. Despite the presence of some degree of heterogeneity in policy coverage, the World Bank database on agricultural incentives developed by Anderson and Nelgen (2012b) provides standardized measures for agricultural policies. These measures provide a synthesis of the set of heterogeneous national agricultural policy incentives in a comparative setting, which reduces the possible violation of SUTVA. We address the "non-interference assumption" by removing from the sample the countries reporting the highest quotas in terms of international trade value in agriculture during the 1990–2010 period. In particular, we remove the top ten exporters and the top ten importers based on trade data from Direction of Trade Statistics (DOTS).[7] This reduces the risk of interference and spillovers caused by policy interventions by the main global exporter and importer countries.

Variables and Data

We use three different sets of data: (*a*) the nominal rate of assistance (NRA) as the treatment variable (T) from the World Bank database "Updated National and Global Estimates of Distortions to Agricultural Incentives, 1955 to 2010" by Anderson and Nelgen (2012b); (*b*) a set of covariates (X) to explain the probability of reaching a specific level of NRA; and (*c*) four outcome variables (Y) used to proxy for the FS dimension. The unit of observations is country-time.

The Treatment: The Nominal Rate of Assistance

Anderson and Nelgen's (2012b) World Bank database provides annual values for a set of

[6] Only weak unconfoundedness is assumed since joint independence of all potential outcomes is not required (Hirano and Imbens 2004).

[7] Note that eight out of ten countries are both main exporters and main importers, namely the United States, Germany, France, Italy, Spain, the Netherlands, Belgium, and China. Brazil and Canada are the other two main exporters, and Japan and the UK are the other two main importers.

standardized measures of policy-related distortions, for a total of eighty-two countries (which together account for over 90% of global agricultural output) and seventy products, over the 1955–2011 period.[8] This database contains aggregate and by-product NRA measures defined as the percentage by which government policies directly raise (or lower) the gross return to producers from a product above the world price: $NRA = [E.P(1+d) - E.P]/E.P$, where E is the exchange rate, d is a distortion due to government interventions, and P is the foreign price of an identical product in the international market (Anderson 2006). Positive values of NRA denote a rise in domestic producers' gross return (the observed price is higher because of the presence of an output subsidy and/or a consumption tax), while negative values denote a lower gross return for domestic producers (the producers receive less than the price for the same product in the absence of government interventions).[9]

Governments can influence agricultural incentives directly through a broad array of policy instruments, which include interventions in both input and output markets (e.g., subsidies, controls over land use, producer and consumer price supports, taxes, food reserves releases), and border measures that have an impact on a country's external balance and terms of trade. Trade policies such as export and import taxes, subsidies, and quantitative restrictions are among the most frequently used instruments and account for 60% of agricultural NRAs at the global level. In contrast, domestic agricultural policies, which provide direct subsidies or tax inputs and outputs, contribute only minimally to price incentives (Anderson, Rausser, and Swinnen 2013).

Collapsing the net effects of multiple policy instruments into a common metric raises issues related to conversion and aggregation. In the first case, the problem is due mainly to the growing importance of agricultural non-tariff barriers (NTBs) such as quantitative restrictions and technical regulations, which complicate the capture of the overall level of protection (Cipollina and Salvatici 2008). The World Bank database deals with this issue through careful domestic to international price comparison of key farm products for a large set of Organisation for Economic Co-operation and Development (OECD) and developing countries, thereby capturing also the domestic price effects of NTBs (Lloyd, Croser, and Anderson 2010). This is accomplished by comparing the domestic and border prices of like products (at similar points in the value chain) for each of the farm industries covered, drawing on national statistical sources supplemented—where necessary—by Food and Agriculture Organization of the United Nations (FAO) data on producer prices and export and import unit values.

In the second case, since policy incentives are calculated at a very detailed level, they need to be summarized into a single aggregate and economically-meaningful measure. The World Bank database computes the overall agricultural sector rate (NRAag) as a weighted average NRA generated by multiplying the value of each primary industry's production share (at farm gate-equivalent undistorted prices) by its corresponding NRA and summing across commodities (Anderson and Nelgen 2012b). Table 1 reports the summary statistics of the NRA for the overall agricultural sector of the sampled countries, over the 1990–2010 period. On average, developed countries protected their agricultural sector, with the highest positive rates registered in Northern European countries (Iceland, Norway, Switzerland, Ireland) and South Korea. Morocco is the exception, being the only developing country with a substantially positive NRA. On the other hand, developing countries have tended to tax their agricultural sector, with the highest negative rates recorded in Sub-Saharan Africa (Ivory Coast, Zimbabwe, Tanzania, and Ethiopia) and Latin America (Argentina, Nicaragua, and Ecuador).

The Covariates

Selection of the covariates is based on the political economy of agricultural and food policies literature (Anderson 2013; Anderson,

[8] The World Bank database on agricultural incentives is not the only attempt to measure policy-induced effects on agricultural market prices. Other initiatives are the Organisation for Economic Co-operation and Development (OECD) Producer and Consumer Support Estimates database for the OECD countries, the FAO Monitoring and Analyzing Food and Agricultural Policies (MAFAP) database for Sub-Saharan countries, and the Inter-American Development Bank (IDB) Producer Support Estimates database for Latin America and the Caribbean. We prefer to use the World Bank database because none of the other data sets provides the country or period coverage required to perform the present analysis.

[9] The border price, used as a benchmark for producer prices when calculating the NRA, is adjusted to take account of all the additional costs generated by the value chain activities and not imputable to the policy interventions (Anderson and Valenzuela 2008).

Table 1. Summary Statistics for the Agricultural Sector NRA of the Sampled Countries (Average Values, 1990–2010)

Country	Mean	S.D.	Min.	Max.	Country	Mean	S.D.	Min.	Max.
Argentina	−0.094	0.091	−0.230	0.004	Mali	−0.020	0.028	−0.099	0.016
Australia	0.024	0.016	0.005	0.064	Mexico	0.140	0.130	−0.151	0.413
Austria	0.420	0.228	0.066	0.821	Morocco	0.508	0.086	0.328	0.667
Bangladesh	−0.020	0.070	−0.154	0.138	Mozambique	0.027	0.037	−0.050	0.090
Benin	−0.013	0.019	−0.069	0.005	New Zealand	0.023	0.014	0.004	0.064
Bulgaria	−0.002	0.090	−0.188	0.183	Nicaragua	−0.091	0.081	−0.229	0.052
Burkina Faso	−0.026	0.054	−0.199	0.021	Nigeria	0.065	0.180	−0.087	0.722
Cameroon	−0.004	0.016	−0.030	0.049	Norway	0.977	0.243	0.613	1.240
Chad	−0.006	0.012	−0.038	0.012	Pakistan	−0.027	0.076	−0.216	0.123
Chile	0.059	0.035	0.004	0.102	Philippines	0.202	0.129	−0.059	0.411
Colombia	0.162	0.090	−0.036	0.341	Poland	0.185	0.135	−0.016	0.596
Czech Rep.	0.206	0.122	0.066	0.484	Portugal	0.264	0.110	0.082	0.438
Denmark	0.340	0.181	0.063	0.697	Romania	0.343	0.251	0.036	0.798
Dominican Rep.	0.036	0.132	−0.203	0.281	Russia	0.204	0.101	0.011	0.419
Ecuador	−0.035	0.124	−0.212	0.219	Senegal	−0.015	0.115	−0.172	0.226
Egypt	−0.036	0.082	−0.202	0.104	Slovakia	0.247	0.124	0.066	0.426
Estonia	0.151	0.154	−0.196	0.488	Slovenia	0.558	0.293	0.092	1.056
Ethiopia	−0.081	0.275	−0.226	0.892	South Africa	0.051	0.070	−0.067	0.213
Finland	0.479	0.377	0.068	1.260	South Korea	0.963	0.291	0.483	1.271
Ghana	0.045	0.136	−0.064	0.468	Sri Lanka	0.041	0.114	−0.221	0.192
Hungary	0.207	0.124	0.065	0.446	Sudan	0.107	0.316	−0.209	0.826
Iceland	0.992	0.287	0.597	1.228	Sweden	0.460	0.298	0.066	1.128
India	0.055	0.124	−0.128	0.260	Switzerland	0.778	0.305	0.469	1.287
Indonesia	−0.014	0.106	−0.218	0.138	Tanzania	−0.112	0.058	−0.174	0.000
Ireland	0.572	0.263	0.078	1.051	Thailand	−0.004	0.061	−0.093	0.149
Ivory Coast	−0.194	0.016	−0.222	−0.169	Togo	−0.015	0.019	−0.072	0.003
Kazakhstan	0.047	0.052	−0.024	0.100	Turkey	0.247	0.113	0.013	0.432
Kenya	0.029	0.063	−0.078	0.158	Uganda	0.001	0.007	−0.022	0.009
Latvia	0.219	0.174	0.032	0.541	Ukraine	−0.030	0.096	−0.192	0.135
Lithuania	0.222	0.198	−0.155	0.653	Vietnam	0.045	0.177	−0.231	0.322
Madagascar	−0.043	0.047	−0.127	0.063	Zambia	−0.079	0.128	−0.224	0.134
Malaysia	−0.008	0.047	−0.134	0.037	Zimbabwe	−0.191	0.042	−0.227	−0.142

Rausser, and Swinnen 2013; Swinnen 2010).[10] Specifically, we use the following variables (see table A.1 in the appendix for additional details and sources): log of real per capita GDP and its squared and cubic power, to control for non-linearities in the anti-trade behavior of the most advanced economies and to facilitate the balancing property as suggested by Dehejia and Wahba (1999) and Dehejia (2005); log of total population and its square to control for country size; log of per capita arable land to control for the relative agricultural comparative advantage; the agricultural total factor productivity growth index to control for the productivity of the agricultural sector; the ratio of food imports to total exports and its square to control for the country's ability to autonomously access the global market and to be less food-dependent; net food exports to control for sectoral trade position; absolute percentage (positive and negative) deviations from the trend in international food prices to control for the presence of asymmetric policy responses to large changes in price levels; and a measure for international food price volatility to control for the second moment of the relationship between the international price dynamics and trade distortions. We include a set of dummies to control for unobservable factors among groups of countries belonging to the same regional area—African countries (base), Asian countries, European transition economies, Latin

[10] Note that the literature on matching provides no guidance on the choice of the conditioning variables that generate identification. The conventional model selection criteria used to choose the variables in the conditioning set do not necessarily work in this context. Including variables that are statistically significant in the treatment choice equation does not guarantee the selection of a satisfying set of conditioning variables, that is, variables that achieve the balancing property (Heckman and Navarro-Lozano 2004).

American countries, and high income countries—and a dummy to capture the effects of the recent food crisis of 2007/2008 (see table A.2 in the appendix for summary statistics).[11]

The Outcome: Dimensions of Food Security

The international community has reached agreement on a definition of FS which emphasizes its multidimensionality. Specifically, FS is described as the condition that "exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (Committee on World Food Security "CFS" 2009). Based on this definition we can identify four pillars of FS: availability, access, utilization, and stability (CFS 2009). Availability is a measure of the amount of physical food available in the population over a certain period of time. The availability of food does not guarantee that everyone will be free from hunger, which is why access matters. The access pillar is related to Sen's Capability Approach framework and refers to people's actual capacities to regularly acquire adequate quantities of food.[12] The third pillar, utilization, is a measure of the population's ability to achieve sufficient nutritional intake and absorption over a given period. The fourth pillar, stability, involves the risk components present in the first three pillars, for example, natural events, man-made shocks, or malfunctioning international markets (Pangaribowo, Gerber, and Torero 2013).

Since Fixed-effects is characterized by multiple dimensions and can be defined at the national, local, household, or individual levels, there is no single available measure that encompasses all of these aspects. The literature provides more than 450 indicators and representation of each pillar by a specific set of variables and indicators (Hoddinott 1999; Cafiero 2013; Pangaribowo, Gerber, and Torero 2013). The set of available choices is limited by data availability. Hence, we chose the following outcome variables for our empirical exercise: supply of food commodities in kilo-calories per person, per year (as a proxy for food availability); depth of the food deficit (food access); prevalence of anemia among children aged under five (food utilization); and per-capita food supply variability (stability; see tables A.1 and A.2 in the appendix for additional details, sources, and summary statistics).

Empirical Results

We conduct an empirical analysis of each dimension of FS, which avoids the use of a composite indicator. Data availability in FS measures constrains us to limit our data set to the sub-period of 1990–2010. To reduce possible sources of bias we omit from the analysis the main importer and exporter countries, which results in a sample of sixty-four countries (table 1).[13] Following Anderson and Nelgen (2012a) and Anderson and Nelgen (2012b), we convert *NRAag* into a nominal assistance coefficient (NAC) to transform the negative values of *NRAag*: $NAC = 1 + \text{NRAag}$. In other words, the threshold between positive and negative support is equal to one: if the NAC is above one, producers receive incentives from government, if it is below one, they are penalized. If the government decides to increase the subsidies (decrease taxes) to the sector, the NAC increases; with higher taxes (lower subsidies), the NAC decreases. The NAC observations before the 5th percentile and after the 95th percentile were removed from the sample in order to clean the data of potential outliers.

Controlling for Endogeneity: Preliminary Regression-Type Estimates

Before moving to the GPS analysis we need first to exclude the risk of potential endogeneity caused by reverse causality between FS and agricultural policy distortions. To this end, for each dimension of FS, we run FE and FE-IV estimates. As the excluded instrument, we use the previous decade's simple

[11] We acknowledge that other determinants (e.g., income distribution or food aid assistance) might improve our matching exercise significantly. However, to our knowledge there are no available datasets that provide yearly information on these variables for all the countries and for the whole period under analysis. Also, we need to consider that there is always a trade-off between increasing the explanatory power through the use of additional covariates and the risk of an over-parameterized model, which in turn could exacerbate the support problem and increase the variance in the propensity score estimates (Bryson, Dorsett, and Purdon 2002).

[12] In the Capability Approach, human well-being can be considered an index of the person's "actual being and doing" (functionings), where capabilities are the substantive freedoms people have reason to value to achieve alternative combinations of functionings (Sen 2001).

[13] Note that their inclusion does not change the empirical outcomes and corresponding DRF significantly. We also repeated the analysis removing all EU member countries: the final results do not change significantly.

moving average of NRA, which is supposed to be correlated with the current level of NRA but uncorrelated with any other determinants of future FS. To control for both observable and unobservable factors that might influence the above relationship, we add to the regressions a set of country-level covariates selected according to the empirical literature on the macro drivers of FS (Garrett and Ruel 1999; Rose 1999; Iram and Butt 2004; Misselhorn 2005; Feleke, Kilmer, and Gladwin 2005; Pangaribowo, Gerber, and Torero 2013), and also country- and time-fixed effects. Specifically, we estimate the following linear relationship for each dimension of FS:

$$f_{id} = \alpha + \beta_1 t_{id} + \beta_2 X_{id} + \theta_i + \theta_d + \epsilon_{id} \tag{10}$$

where f is our FS outcome; t is NAC; $\boldsymbol{X}$ is a bundle of standard control covariates; θ_i and θ_d are, respectively, country- and time-fixed effects; and ϵ is the error component. Countries are indexed $i = 1, \ldots, N$ and observed once per period $d = 1, \ldots, D$. In order to capture the non-linear relationship between agricultural incentives and FS, we also run the model including the square and cubic terms of NAC in equation (10).

Table 2 reports the outcomes of the above panel regressions for the first dimension of FS, that is, food availability (proxied by food supply in kcal/capita/day); in the supplementary material online we present the results for the other three dimensions.[14] The coefficients of the determinants of food availability are highly significant in both the baseline FE and the IV-FE estimates. The NAC always has a positive and significant effect on food availability in the FE regressions (columns 1–3) but loses significance in the IV-FE model (columns 4–6) with the introduction of the squared and cubic powers.[15] More importantly, the Hausman test does not reject the null hypothesis that NAC can be treated as exogenous. This means that the FE and IV-FE estimates are not significantly different, and the relationship between agricultural incentives and food availability is not affected by reverse causality.

As a falsification test, we investigate whether NRA at time $d + 1$ influences FS outcomes at time d. As suggested by Rothstein (2010) and Wooldridge (2010), testing for feedback effects is another way of controlling for the strict exogeneity of our treatment variable, and excludes the possibility of covariance among trends or other omitted variables. The lack of endogeneity is confirmed by the results in table 2, columns 7–9: the coefficients of future adoption of agricultural incentives are close to zero and never significant. These results are confirmed for all the FS dimensions.[16] However, regression-type analyses do not rule out the risk of misspecification due to the self-selection bias, induced by incomparable observations.

GPS Estimation and Balancing Property

Moving to the GPS exercise, we first regress our measure of agricultural (dis)incentives on a set of pre-treatment observable characteristics (equation 5). Since the joint Jarque-Bera normality test provides strong support for the null hypothesis of a normal distribution of our treatment variable, in this first stage, we use Ordinary Least Squares (OLS).[17] Table 3 presents the results.

The R-squared is quite high and consistent with that obtained in similar empirical GPS exercises (Becker, Egger, and von Ehrlich 2012; Serrano-Domingo and Requena-Silvente 2013; Magrini, Montalbano, and Nenci 2017), and the estimated coefficients of the covariates are reasonable. The higher the NAC, the higher is the country's per capita income (although at a decreasing rate), and the lower the country's comparative advantage in agriculture (proxied by arable land per capita). We also found a negative relationship between NAC and the country dimension (proxied by population size). Countries characterized by high dependence

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[14] It should be noted that while the economic literature provides many examples of a linear specification between food availability and its determinants, in the case of the other dimensions—food access, utilization, and stability—we lack a robust theoretical model framework (Pangaribowo, Gerber, and Torero 2013).

[15] All the multivariate F-tests for excluded instruments reject the null hypothesis that the instruments are not correlated with the endogenous regressors. The results of the F-tests are equal to 180.49, 92.74, and 64.71 for columns (4), (5), and (6), respectively, and confirm that the instruments are relevant. However, there is a need for some caution because there are no tests to verify the validity of the NRA moving average as an instrument.

[16] The details are available in a supplementary material online.

[17] A zero-skewness log transformation was applied to normalize the NAC distribution. The p-value is 0.611, which is well above the standard 5% statistical significance threshold.

Table 2. Panel Fixed-Effects Estimates of Food Availability

	Fixed-effects			IV Fixed-effects			Fixed-effects placebo		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NAC	0.030***	0.115***	0.257***	0.034**	0.076	−4.384	0.024***	0.107***	0.290***
	(0.004)	(0.019)	(0.095)	(0.017)	(0.074)	(4.101)	(0.006)	(0.023)	(0.083)
$NAC(d+1)$							0.009	0.03	0
							(0.007)	(0.019)	(0.053)
NAC^2		−0.031***	−0.133**		−0.014	3.101		−0.030***	−0.161***
		(0.006)	(0.064)		(0.024)	(2.918)		(0.007)	(0.052)
$NAC^2(d+1)$								−0.006	0.015
								(0.005)	(0.033)
NAC^3			0.023*			−0.682			0.029***
			(0.014)			(0.653)			(0.011)
$NAC^3(d+1)$									−0.004
									(0.006)
ln real pc GDP	0.503***	0.501***	0.504***	0.502***	0.495***	0.499***	0.507***	0.504***	0.506***
	(0.064)	(0.066	(0.065	(0.05	(0.053	(0.048	(0.074	(0.076	(0.075
ln real pc GDP^2	−0.026***	−0.027***	−0.027***	−0.027***	−0.026***	−0.025***	−0.026***	−0.026***	−0.027***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)
ln pc arable land	0.043***	0.043***	0.043***	0.042***	0.042***	0.049***	0.041***	0.041***	0.041***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)
Agr TFP	0.077***	0.080***	0.081***	0.077***	0.078***	0.036	0.074***	0.077***	0.078***
	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)	(0.039)	(0.027)	(0.029)	(0.028)
ln pop	0.658***	0.665***	0.669***	0.633***	0.640***	0.474**	0.684***	0.697***	0.701***
	(0.083)	(0.079)	(0.079)	(0.103)	(0.109)	(0.238)	(0.100)	(0.095)	(0.096)
ln pop^2	−0.033***	−0.034***	−0.034***	−0.032***	−0.033***	−0.028**	−0.035***	−0.035***	−0.035***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.011)	(0.006)	(0.006)	(0.006)
Country fe	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time fe	yes	yes	yes	yes	yes	yes	yes	yes	yes
No. of observations	1098	1098	1098	1091	1091	1091	1061	1061	1061
Adj. R^2	0.514	0.517	0.517	0.513	0.515	0.451	0.503	0.508	0.509
Hausman test P				0.783	0.666	0.253			

Note: $(NAC) = (1 + NRAag)$; standard errors (in parenthesis) are calculated using a Driscoll-Kraay estimator for addressing both spatial and temporal dependence. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Generalized Propensity Score Estimates (Dep. Variable: NAC)

Covariates	Coef.	SE (robust)
L.ln real pc gdp	0.979**	0.463
L.ln real pc gdp^2	−0.115**	0.056
L.ln real pc gdp^3	0.005**	0.002
L.ln pc arable land	−0.037***	0.006
L.ln pop	−0.099***	0.025
L.ln pop^2	0.005***	0.001
L. Agr.TFP	−0.015	0.035
L.food import/total exports	−0.720*	0.406
L.food import/total exports^2	2.805	1.799
L.net food exports	−0.059***	0.008
L.pos dev food prices	−0.445***	0.143
L.neg dev food prices	−0.303***	0.108
food price volatility	−1.195***	0.469
group 2 -Asian DCs	−0.072***	0.017
group 3 - Latin American DCs	−0.072***	0.018
group 4 - European Transition Economies	0.036*	0.020
group 5 - High-income Countries	0.014	0.028
food crisis	−0.045***	0.015
cons	−2.265*	1.311
No. of observations	1076	
adj. R^2	0.429	

Note: Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

on food imports with respect to their total exports tend to have lower levels for NAC since they are aimed at reducing the domestic prices of imported goods (Valdés and Foster 2012).

The "anti-trade pattern" of agricultural policies is confirmed because countries with higher values for net food exports tend to provide less protection. The NACs are negatively correlated with positive and negative deviations of international prices from their trend. This is consistent with the governments' goal of stabilizing the domestic market since food imports tend to decline during price spikes, and export taxes tend to be increased (Anderson 2013; Anderson and Nelgen 2012b). Comparing the absolute values of the coefficients suggests that policy makers react more strongly to price spikes compared to price troughs. International food price volatility has a negative impact on the NACs, highlighting a strong correlation with trade distortions, which imply lower gross returns for domestic producers, probably because of the well-known depressive impact on the consumption behavior of price volatility. The signs of the coefficients of the regional dummies are consistent with other well-known policy patterns such as the "development pattern" in which richer countries tend to provide higher protection for domestic producers, while developing countries tend to maintain lower levels of NAC.[18] Finally, NACs are lower, on average and *ceteris paribus*, during "food crisis" years.

The second step in our impact evaluation exercise is to test the "balancing property." We compare the covariates across groups with and without the GPS correction. Then we conduct a series of two-sided t-tests across groups, for each covariate. Table A.3 in the appendix presents the results. We have four approximately similar-sized groups based on their actual NAC.[19] Before controlling for GPS there are significant differences across the treatment groups with respect to the covariates (t-values—reported in bold—indicate the presence of statistically significant differences at the 5% level). The average t-stat is 4.58 (well above the 1.96 threshold), and forty-eight out of seventy-two tests reject the balancing assumption. If we condition on

[18] Given the significance of trade within geographic regions, and its potential for violating the SUTVA, we re-ran the model/regression, dropping the regional dummies to reduce the probability of matching countries being in the same area. Omitting the regional dummies did not change the final results but slightly reduced the first-stage fitting since they help to capture some unobservable factors. The results are provided in the supplementary material online.

[19] We ran t-tests for different numbers of groups before choosing the best combinations in terms of the balancing property.

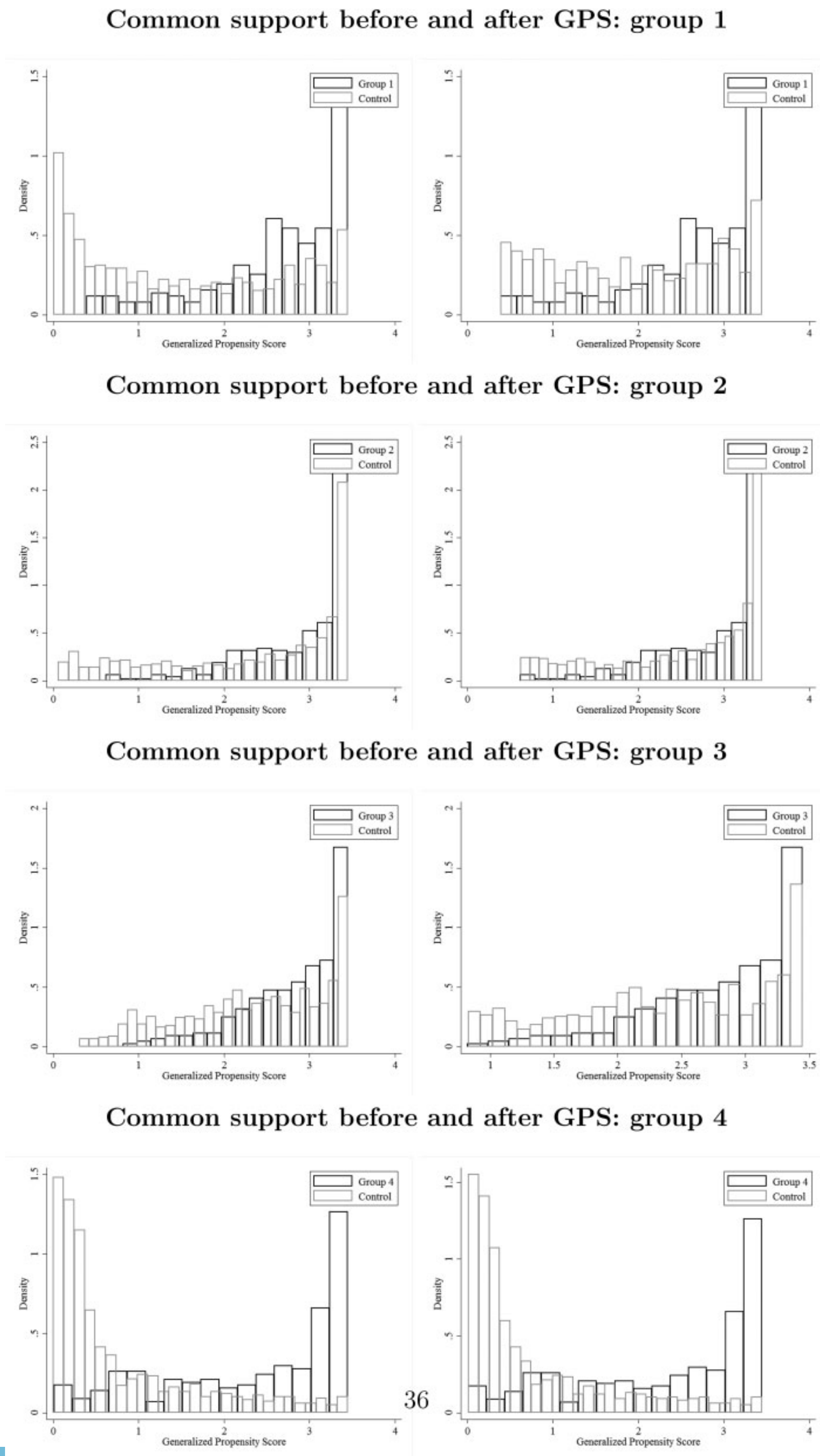

Figure 1. Common support before and after GPS

Source: Authors' calculations. Left-hand side graphs are before GPS correction; right-hand side graphs are after GPS correction.

the value of the GPS score—building eight strata—and impose the common support condition (eliminating those control observations outside GPS support of the treated groups), we observe an evident improvement in the balancing of the covariates. The average t-stat reduces to 0.92, and balancing is rejected in only four out of the seventy-two tests. Figure 1 provides a visual overview of the differences in common support before and after GPS correction. As shown by the pictures, the GPS distribution between actual and control groups differs substantively before the pruning (see left-hand side panels), whereas there is a clear overlap after it (see right-hand side panels). Table A.4 in the appendix reports the final group-strata data structure, whereas figure A.1 in the appendix shows the map of sample countries with the percentage of observations excluded based on common support.

The Dose-Response Function

The last step is to estimate the DRF to assess whether there is a causal link between NAC changes and each dimension of the FS (equation 7). We test a polynomial parameterization of the conditional expectation of the outcome as a function of the observed treatment and the estimated GPS. While the GPS coefficients control for selection bias in the different treatment intensities, the interaction term shows the marginal impact of the treatment relative to the GPS. Thus, if there were selection bias between the level of agricultural incentives and the FS dimension, both the GPS and the interaction coefficients would be statistically significant. Following Bia and Mattei (2008) we use bootstrap methods to obtain the DRF standard errors and confidence intervals.

Following Egger, von Ehrlich, and Nelson (2012), we test our DRF for different orders of the polynomial terms, dropping those that proved insignificant. The results are summarized in tables A.5, A.6, A.7, and A.8 in the appendix. As in the first stage, the R-squared is relatively high and consistent with previous GPS exercises (Becker, Egger, and von Ehrlich 2012; Serrano-Domingo and Requena-Silvente 2013; Magrini, Montalbano, and Nenci 2017). Further, the coefficients of the GPS and the interaction terms are always highly significant, confirming our initial hypothesis about the existence of self-selection into different agricultural incentive intensities.

The upper panels of figures 2–5 report the DRFs—which provide graphical representations of the relationship between agricultural incentives and FS; the lower panels depict the TEF, that is, the first derivative of the respective DRF. The corresponding standard errors and 90% confidence intervals of both functions are also reported (dotted lines in the figures). For the first dimension of FS, we assume that the aim of policy intervention is to increase food availability. Indeed, according to the estimated DRF in figure 2, the highest level of food supply is registered when the agricultural sector receives support of around 20%. We find also that the highest marginal benefit—on average—is obtained by eliminating residual taxation and moving to limited support, with NAC values ranging from 0.9 to 1.2. However, the estimated DRF shows also that if the NAC value is greater than 1.2—equivalent to strong support for producers—the level of food availability starts to decrease (as shown by the negative values of the TEF).

With respect to the access and utilization dimensions, policy goals are associated with minimizing the response value. For food access, the depth of the food deficit is minimized for a NAC equal to 1.15 (see figure 3, upper panel). This again implies that limited support has a positive impact, while both taxation and major support increase the food deficit. The pattern is similar for food utilization since the lowest value for infant anemia corresponds to an NAC treatment of 1.16; the worst performance is for an NAC of less than 1 or higher than 1.3 (see figure 4, upper panel). Note that although the flexible nonparametric approach imposes no a priori functional form on the relationship between the treatment and the FS outcomes, the empirical results appear to be consistent across these three dimensions. The DRFs/TEFs show broadly similar patterns, while the thresholds for the relationship between agricultural incentives and FS are not significantly different. Some caution is needed for the stability dimension. The specialized literature relates it to the risk components for all FS dimensions, for example, natural events, man-made shocks, and malfunctioning international markets (Pangaribowo, Gerber, and Torero 2013). Due to data constraints we proxied this by the variability of per capita food supply. The DRF shows that the lowest expected per capita food supply variability is associated with moderate taxation (NAC equal to 0.95) or very substantial support (around

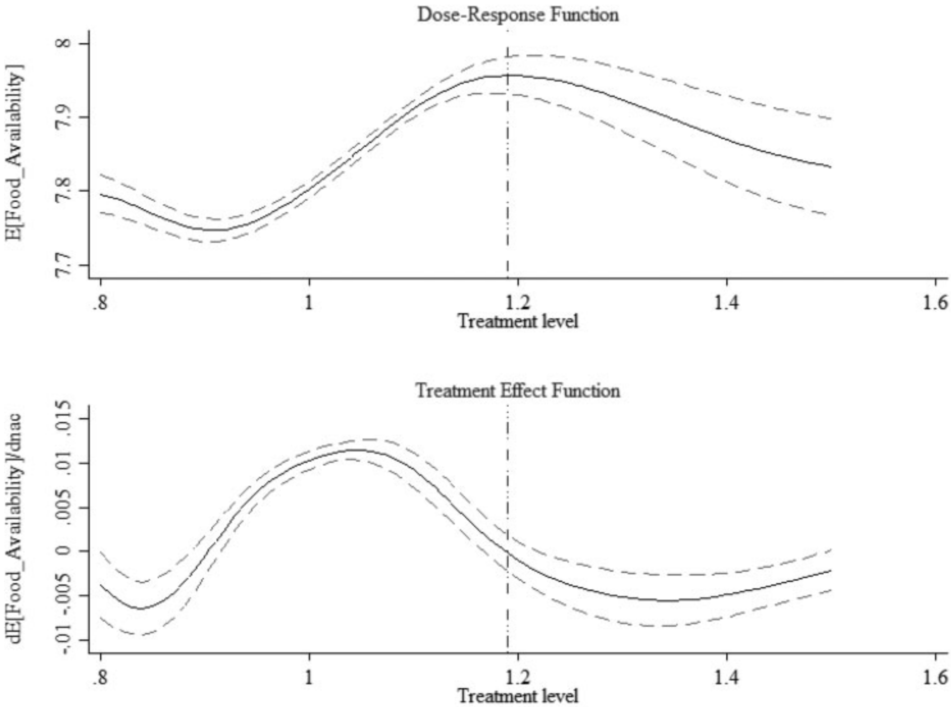

Figure 2. The impact of agricultural (dis)incentives on food availability

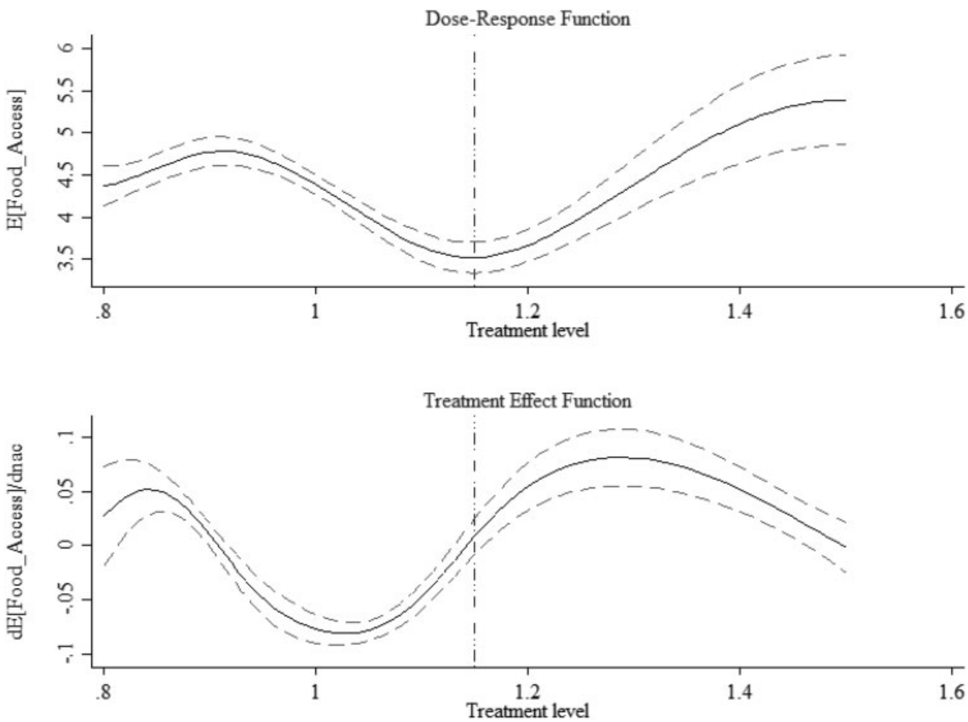

Figure 3. The impact of agricultural (dis)incentives on food access

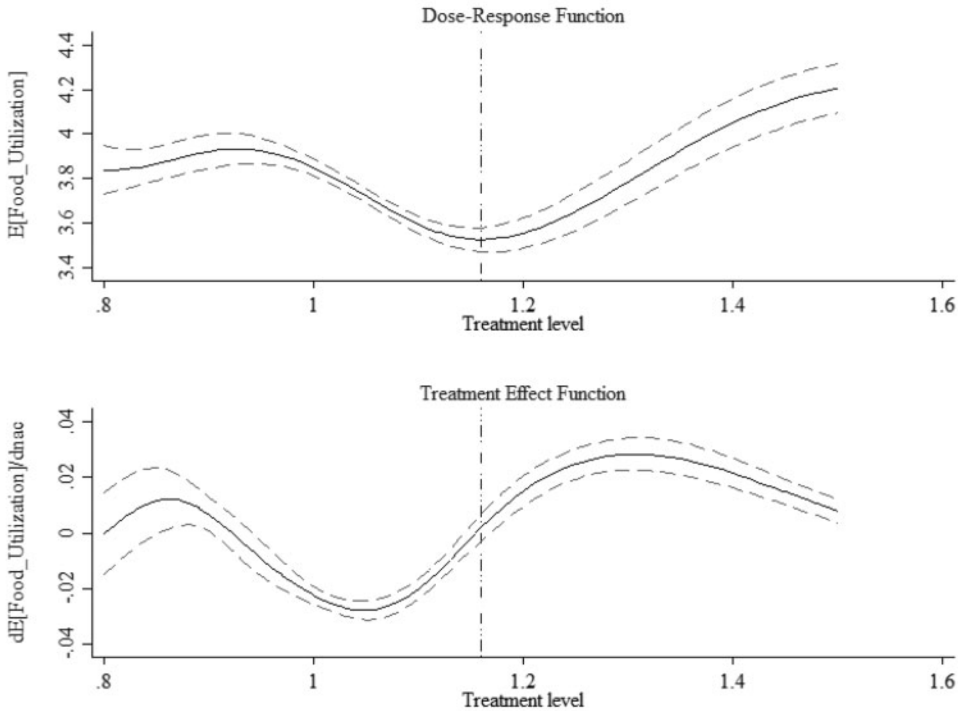

Figure 4. The impact of agricultural (dis)incentives on food utilization

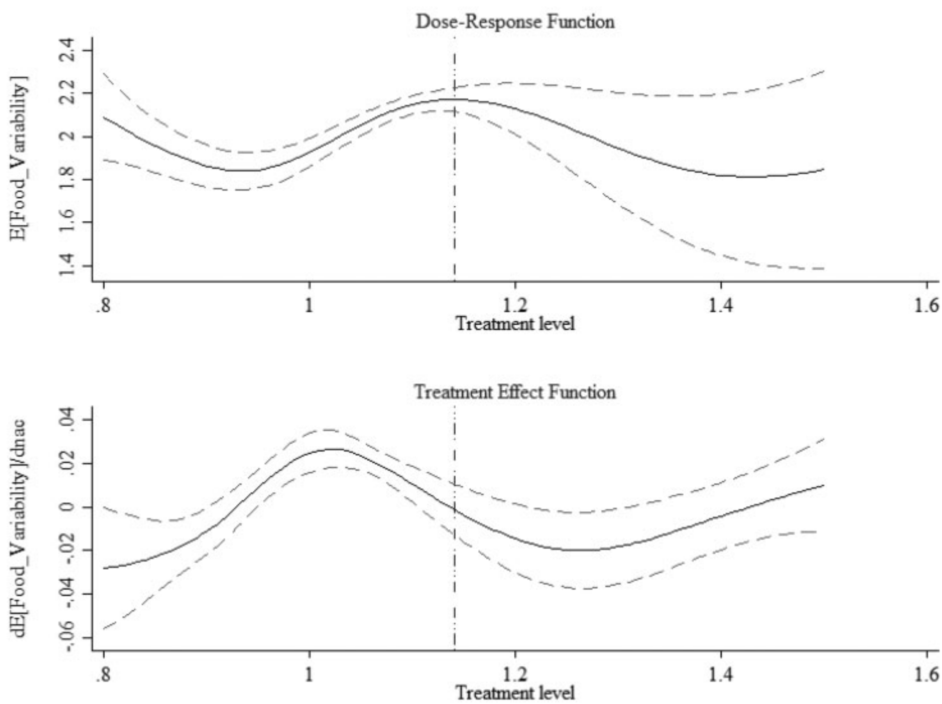

Figure 5. The impact of agricultural (dis)incentives on food variability

Table 4. NAC Frequencies by Countries and Regional Groups, Percentage (1990–2010)

Country	Below 1	Btw 1-1.2	Above 1.2	Country	Below 1	Btw 1-1.2	Above 1.2	Country	Below 1	Btw 1-1.2	Above 1.2
Argentina	**95**	5	0	Australia	0	**100**	0	Austria	0	19	**81**
Bangladesh	**55**	45	0	Chile	0	**100**	0	Czech Rep.	0	47	**53**
Benin	**69**	31	0	Colombia	5	**70**	25	Denmark	0	29	**71**
Bulgaria	**53**	47	0	Dominican Rep.	35	**60**	5	Finland	0	24	**76**
Burkina Faso	**80**	20	0	Estonia	16	**53**	32	Hungary	0	47	**53**
Cameroon	**65**	35	0	India	40	**45**	15	Iceland	0	0	**100**
Chad	**63**	38	0	Kazakhstan	40	**60**	0	Ireland	0	19	**81**
Ecuador	**68**	26	5	Kenya	40	**60**	0	Lithuania	16	37	**47**
Egypt	**75**	25	0	Latvia	11	**56**	33	Morocco	0	0	**100**
Ethiopia	**85**	0	15	Malaysia	25	**75**	0	Norway	0	0	**100**
Ghana	**55**	30	15	Mexico	14	**57**	29	Philippines	5	45	**50**
Indonesia	**60**	40	0	Mozambique	25	**75**	0	Portugal	0	29	**71**
Ivory Coast	**100**	0	0	New Zealand	0	**100**	0	Romania	0	42	**58**
Madagascar	**75**	25	0	Nigeria	40	**45**	15	Russia	11	42	**47**
Mali	**80**	20	0	Poland	11	**63**	26	Slovakia	0	38	**63**
Nicaragua	**95**	5	0	South Africa	19	**76**	5	Slovenia	0	21	**79**
Pakistan	**70**	30	0	Sri Lanka	30	**70**	0	South Korea	0	0	**100**
Senegal	**63**	31	6	Uganda	38	**63**	0	Sweden	0	19	**81**
Sudan	**75**	5	20	**Asia**	38	**44**	18	Switzerland	0	0	**100**
Tanzania	**100**	0	0	**South America**	40	**52**	8	Turkey	0	29	**71**
Thailand	**60**	40	0	**Transition Ctrs**	14	**43**	42	**Developed Ctrs**	0	32	**68**
Togo	**85**	15	0	**World average**	31	**37**	32				
Ukraine	**63**	37	0								
Vietnam	**56**	19	25								
Zambia	**94**	6	0								
Zimbabwe	**100**	0	0								
Africa	**65**	28	7								

1.4), although in this latter case the confidence intervals are pronounced and less reliable. It should be noted that treatment levels in the range associated with the best performance in the case of the other FS dimensions, in this case produce the worst result.

The consistency across the first three DRFs allows us to cluster our sample countries based on past observed NAC frequency in order to provide some insight into conditional future FS performances.[20] Table 4 reports countries' relative frequencies for NAC. These values are observed within the ranges obtained by applying the empirically-estimated thresholds using the DRF for the availability dimension (i.e., number of times the NAC is below 1, between 1 and 1.2 and above 1.2). The left panel includes the majority (twenty-six) of our sample countries. Most have a NAC below 1 for most of the time (Ivory Coast, Tanzania, Zimbabwe, Argentina, Nicaragua, and Zambia all over the period). The prevailing regime in these countries of negative price support is likely to determine lower outcomes in terms of FS, *ceteris paribus*. Note that Africa is the only macro-regional area with NAC below 1 most of the time, on average. The right-hand panel includes the twenty countries reporting the highest frequency of NAC, in the range above 1.2 (Iceland, Morocco, Norway, South Korea, and Switzerland register NAC above 1.2 all over the period). Also, in this case the prevailing regime is supposed to determine a lower expected FS, *ceteris paribus*. The middle panel includes fourteen countries where the highest frequency of NAC is in the range 1 to 1.2. According to our analysis, this frequency is associated with the best expected impact in terms of food availability.

Conclusions and Policy Implications

Agricultural policies affect the market structure, productivity, and composition of agricultural output, as well as the variety, quality, and safety of food products and the composition of people's diets. To varying degrees, these factors influence all FS dimensions. Existing in-depth country-level case studies take account of the historical, political, and institutional contexts in the link between agricultural incentives and FS but have found it difficult to attribute causality, as well as to provide an adequate view of global trends and potential counterfactuals. This paper filled this gap by investigating whether countries following different agricultural policy strategies differ in their FS performance. We applied GPS, which is a non-parametric method for causal inference in quasi-experimental settings with continuous treatment. Since agricultural policy interventions are not random and depend on national tendencies to intervene in the domestic market, GPS allows possible sources of selection bias, which might be driving empirical estimates, to be addressed.

Our results show that agricultural (dis)incentives matter and that their impact on FS varies in a non-linear way with the level of intensity. We showed that taxation of the primary sector (NAC lower than 1) has a consistent negative impact on the four FS dimensions analyzed. We found also that countries providing moderate support within a limited range to the primary sector tend to do better on most FS dimensions (food availability, access, and utilization) with the best performance recorded for NAC values greater than 1 but less than 1.3. More generally, our empirical analysis confirms that achieving FS is complex and there are no one-size-fits-all solutions.

There are two major policy implications. First, taxing agricultural producers to obtain additional resources for investment in (allegedly) more dynamic sectors comes at a price in terms of FS. This is in line with the findings in Anderson, Rausser, and Swinnen (2013), which show that taxation can harm the welfare of both producers and consumers. For producers it reduces both profits and incentives to respond to market signals. In addition, if taxation discourages farming activity, it can affect poor consumers negatively due to falls in demand for farm labor, and wages for unskilled workers in both farm and non-farm jobs. Therefore, while poor households might benefit from taxation if it contributes to reducing food prices (e.g., an export tax or an import subsidy), they lose earnings if they are suppliers of unskilled labor. The net effect depends on the relative importance of the agricultural sector in the economy. Since our sample includes many developing countries—especially from Asia and Africa—where the agricultural sector accounts for the majority of employment, it is not surprising that our results show a net loss in terms of FS performance as a consequence of agricultural disincentives.

[20] Since the average values are influenced by outliers (i.e., extreme values that could be interpreted as a shock), we use the number of times a country has maintained its policy stance (i.e., relative frequency) to proxy for observed agricultural policy.

The second policy implication is that the positive impact of moderate support to agricultural producers provides opportunities for the use of public interventions in relation to agriculture. This might be consistent with requests from developing countries for a "development box" within WTO negotiations. However, too much support for producers comes at the cost of aggregate FS performance, which might counterbalance the initial benefits or be more damaging than taxation. Our empirical exercise shows that excessive support to the agricultural sector could be as damaging as an anti-agriculture bias in domestic policy. This is a particularly relevant issue for those poor countries—especially in Sub-Saharan Africa—that have chosen to tackle the recent food price crisis with extremely costly and frequently ineffective policy interventions to protect domestic producers, such as the accumulation of excessive food stocks based on governments buying from farmers at prices well above the market equilibrium, or the (re-)introduction of large-input subsidy programs.

Our analysis does not allow normative implications since it does not take account of treatment costs. Also, using a single agricultural incentives metric provides no indications as to which policy measures are the most effective. However, our results are relevant for policy since we introduce an empirical framework able to quantify, net of self-selection bias, the extent to which agricultural policies could influence food insecurity at the aggregate level. These results justify further analyses focusing on specific policy instruments and actual policy mixes at the country level.

Supplementary Material

Supplementary material is available at *American Journal of Agricultural Economics* online.

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Appendix

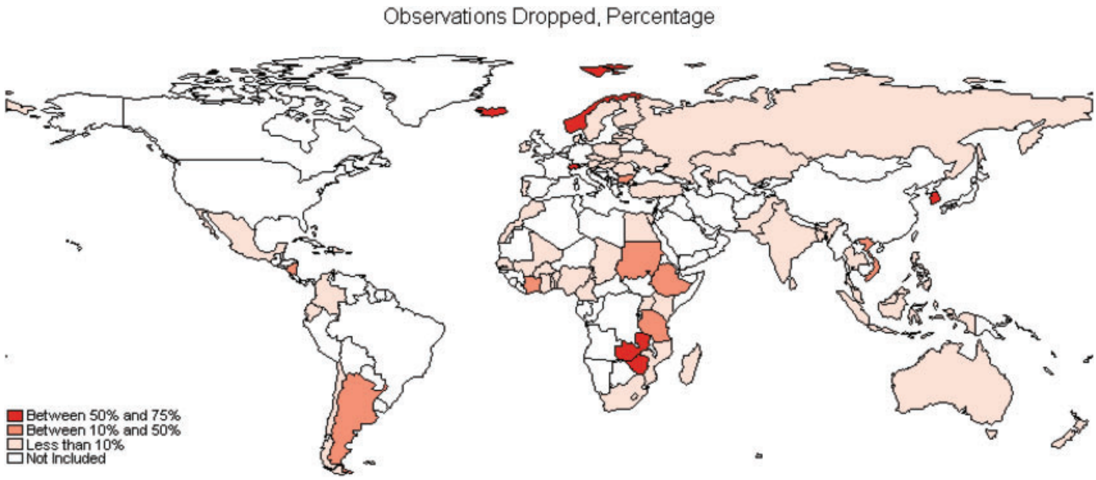

Figure A.1. Map of countries (percentage of observations excluded by the common support)

Source: Authors' calculations.

Table A.1. Variables and Data

Type	Variable (annual data)	Source
Agricultural incentives (treatment)	*Nominal Rates of Assistance (NRAag):* Value of production-weighted average NRA all (primary) Agriculture, total for covered and non-covered and non-product-specific assistance.	World Bank dataset (Anderson and Nelgen, 2012, “Updated National and Global Estimates of Distortions to Agricultural Incentives, 1955 to 2010”)
Observable characteristics (covariates)	*Real per capita GDP (2005 International dollar per person).*	Penn World Table (Heston, Summers and Aten, 2012, ”Penn World Table Version 7.1”, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, November)
	Population (in thousands).	World Bank - World Development Indicators
	Per capita arable land (hectares per person).	World Bank - World Development Indicators
	Agricultural Total Factor Productivity (TFP) growth index (base year 1961=100).	United States Department of Agriculture - Economic Research Service
	(Country) Food imports over total exports.	FAOSTAT; IMF DOTS
	Net food exports.	FAOSTAT
	Deviation of international food prices from trend (positive and negative, percentage).	World Bank - GEM Commodity Price Data
	International food price volatility.	FAOSTAT
	Regional group dummy: African Developing Countries (Group 1); Asian Developing Countries (Group 2); Latin American Developing Countries (Group 3); European Transition Economies (Group4); High-income Countries (Group 5).	World Bank dataset (Anderson and Nelgen, 2012
	Food crisis dummy (1 if year 2007 and 2008).	Authors calculation
Food Security dimensions (outcome):		
Availability	*Food supply (in kcal/capita/day).*	FAO - Food Balance Sheets
Access	*Depth of food deficit (kilocalories per person per day).*	World Bank - World Development Indicators
Utilization	*Prevalence of anemia among children (percentage of children under 5).*	World Bank - World Development Indicators
Stability	*Per capita food supply variability.*	FAOSTAT

Table A.2. Summary Statistics of Covariates and Outcomes

	Mean	S.D.	Min.	Max.	Obs.
Covariates					
Real per-capita GDP	9688.87	11136.77	323.26	51791.63	1076
Population	52592.55	137895.10	269.00	1156898.00	1076
Per-capita arable land	0.328	0.348	0.030	2.807	1076
Agricultural TFP	110.74	15.85	49.13	178.52	1076
Food import/total exports	0.016	0.024	0.001	0.260	1074
Pos. deviation of int.l food prices	0.010	0.030	0.000	0.142	1076
Neg. deviation of int.l food prices	0.050	0.041	0.000	0.138	1076
Food price volatility	0.021	0.009	0.006	0.050	1076
Net Food Exports	1.731	2.305	0.013	24.346	1076
Group 1 - African DCs	0.332	0.471	0.000	1.000	1076
Group 2 - Asian DCs	0.170	0.376	0.000	1.000	1076
Group 3 - Latin American DCs	0.121	0.326	0.000	1.000	1076
Group 4 - European Transition Economies	0.204	0.403	0.000	1.000	1076
Group 5 - High-income Countries	0.173	0.378	0.000	1.000	1076
Food Crisis	0.091	0.288	0.000	1.000	1076
FS Outcomes					
Food Supply (in Kcal/capita/day)	2724.691	524.204	1557.000	3826.000	1047
Depth of Food Deficit (kcal/capita/day)	98.16802	110.2965	1	615	988
Prevalence of anemia among children	42.40548	24.40874	9.4	89.5	1076
Per capita Food Supply Variability	12.66497	13.36718	0.5094946	81.39553	1048

Table A.3. Differences in the covariates by Treatment Levels before and after Balancing on the GPS (T-stats for Equality of Means)

	Prior to balancing on the GPS				After balancing on the GPS			
Covariates	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
L.ln real pc gdp	**14.006**	**8.181**	**5.660**	**17.212**	1.855	1.308	1.475	0.752
L.ln real pc gdp^2	**14.065**	**7.873**	**5.193**	**17.521**	1.823	1.152	1.417	0.639
L.ln real pc gdp^3	**14.042**	**7.520**	**4.702**	**17.713**	1.785	0.992	1.350	0.525
L.ln pc arable land	**2.231**	**3.663**	**2.064**	0.646	1.278	1.552	1.927	1.200
L.pos dev food prices	0.868	1.201	**3.367**	1.282	0.284	0.209	1.024	0.039
L.neg dev food prices	1.023	0.239	**2.023**	0.758	0.465	0.126	0.188	0.434
food price volatility	0.936	0.531	**2.190**	0.719	0.239	0.036	0.424	1.073
food crisis	0.122	1.101	**3.069**	1.836	0.180	0.400	0.621	1.240
L.Agr.TFP	0.627	**2.107**	1.360	**2.844**	0.370	0.419	1.198	1.731
group 2 -Asian DCs	**2.866**	0.609	0.609	**4.104**	0.341	0.097	0.894	0.060
group 3 - Latin American DCs	**2.707**	**3.144**	**4.910**	**4.465**	0.078	1.612	1.538	0.389
group 4 - European Transition Economies	**6.029**	**7.515**	**6.397**	**7.140**	0.202	**2.273**	0.420	0.371
group 5 - High-income Countries	**8.968**	1.396	**2.519**	**13.593**	0.876	**1.995**	0.607	0.473
L.net food exports	**4.041**	1.903	0.352	**6.379**	0.692	0.518	0.934	0.437
L.food import/total exports	**5.483**	**6.258**	**4.704**	**7.057**	1.369	1.593	1.120	0.924
L.food import/total exports^2	**2.222**	**4.563**	**2.882**	**3.892**	1.072	1.365	0.883	0.806
L.pop	**6.393**	0.960	1.827	**7.315**	1.333	**2.019**	0.782	1.255
L.pop^2	**6.151**	1.335	1.949	**6.799**	1.346	**2.017**	0.786	1.154
No. of observations	268	268	268	268	260	254	210	115
Mean t-value	4.582				0.922			

Note: T-values reported in bold face indicate null rejections at the 5% level of significance.

Table A.4. The Final Group-Strata Structure

Strata	Control1	Group1	Control2	Group2	Control3	Group3	Control4	Group4
1	200	31	88	31	218	28	410	15
2	134	30	75	31	96	27	77	14
3	52	31	71	31	42	27	28	14
4	35	30	70	30	44	27	72	14
5	41	30	60	31	54	27	28	15
6	43	31	63	31	67	27	38	14
7	46	30	84	31	31	27	18	14
8	26	30	63	30	51	27	34	14

Table A.5. DRF Estimation for Food Availability

Food availability	Coef.	SE (robust)
NAC	6.427***	1.939
NAC^2	−5.230***	1.555
NAC^3	1.359***	0.403
GPS	−0.383***	0.072
GPS^2	−0.063	0.042
GPS^3	0.014**	0.007
*NAC*GPS*	0.407***	0.035
cons	5.361***	0.769
No. of observations	824	
Adj R^2	0.31	

Note: $(NAC) = (1 + NRA)$. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.6. DRF Estimation for Food Access

Food Access	Coef.	SE (robust)
NAC	−82.465***	22.066
NAC^2	73.761***	18.439
NAC^3	−20.789***	4.993
GPS	3.427***	0.634
GPS^2	0.596**	0.348
GPS^3	−0.112**	0.059
*NAC*GPS*	−4.013***	0.273
cons	33.418***	8.411
No. of observations	763	
Adj R^2	0.273	

Note: $(NAC) = (1 + NRA)$. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.7. DRF Estimation for Food Utilization

Food utilization	Coef.	SE (robust)
NAC	−15.475***	5.201
NAC^2	13.617***	4.151
NAC^3	−3.728***	1.071
GPS	0.681***	0.196
GPS^2	0.269***	0.115
GPS^3	−0.038**	0.020
*NAC*GPS*	−1.124***	0.093
cons	9.412***	2.082
No. of observations	839	
Adj R^2	0.197	

Note: $(NAC) = (1 + NRA)$. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.8. DRF Estimation for Food Variability

Food Variability	Coef.	SE (robust)
NAC	−7.541***	1.797
NAC^2	3.035***	0.689
GPS	−0.985***	0.237
GPS^2	−0.055	0.035
*NAC*GPS*	1.208***	0.194
cons	6.257***	1.043
No. of observations	823	
Adj R^2	0.087	

Note: $(NAC) = (1 + NRA)$. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.