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How Much Does Economic Growth Contribute to Child Stunting Reductions?

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Abstract: The role of economic growth in reducing child undernutrition remains an open and highly debated question that holds important implications for food security strategies. The empirical evidence has been quite contrasted, primarily in regard to the magnitude of the impacts. Yet, most studies have not (appropriately) accounted for the reverse causality between economic growth and child stunting. Using a dataset of 74 developing countries observed between 1984 and 2014, this paper develops a novel approach accounting for the reverse causal effect of stunting on GDP per capita and finds that the impacts of economic growth are much lower than estimated in most previous studies. A 10% increase in GDP per capita reduces child stunting prevalence by 2.7%. In other words, economic growth is modestly pro-poor. We also estimate that a percentage point increase in child stunting prevalence results in a 0.4% decrease in GDP per capita. A back-of-the-envelope calculation suggests that stunting costs on average about 13.5% of GDP per capita in developing countries.

Keywords: economic growth; child stunting; nutrition; reverse causality

JEL Classification: O11; O13

1. Introduction

There is a raging debate in the literature on whether the contribution of economic growth to child stunting reductions is actually large (e.g., Ruel et al. 2013; Vollmer et al. 2014a, 2014b, 2016; Alderman et al. 2014; Smith and Haddad 2015; O'Connell and Smith 2016). This debate has prime policy implications for the relative role given to pro-poor growth strategies to reduce child undernutrition and the need for complementary direct nutritional investments; by extension, it affects how limited financial resources are competitively allocated between different types of investments. Given the lack of consensus on this debate and its policy importance, this paper revisits the relationship between economic growth and child stunting.

The relationship between increased national income and nutrition functions through two complementary channels. When economic growth stimulates average incomes, populations may spend a larger part of their incomes to the consumption of health and nutrition relevant goods and services. Increased GDP may also boost the provision of nutrition-relevant services and social and health infrastructures as richer governments may dedicate higher public spending towards these investments. Such links, however, may be weaker than expected. For instance, if economic growth is associated with rising income inequality, the poorest may not capture the benefits of increased national income.

The empirical literature[1] has provided a wide range of estimates contributing to the lack of consensus. For example, Ruel et al. (2013) find a prominent role of economic growth[2] in that a 10% increase in GDP per capita would lead to a 6% reduction in stunting prevalence. This is in line with several studies (Smith and Haddad 2015; O'Connell and Smith 2016). Mary et al. (2018b) find that the contribution of economic growth may even be higher (i.e., a 10% increase in GDP per capita would decrease child stunting prevalence by 7.3%).

By contrast, Vollmer et al. (2014a) find that the association between economic growth and early childhood undernutrition is quantitatively very small (if not null). Harttgen et al. (2013) also find economic growth has limited positive impacts on the odds of being stunted in Sub-Saharan Africa. Both studies rely on multilevel modeling combining micro- and macro-data that has however attracted criticism (Alderman et al. 2014). In particular, when combining both data types, the little cross-country variation likely exacerbates the measurement error bias and makes it difficult to document strong associations with individual-level nutrition outcomes (Alderman et al. 2014). Several country case-studies also report that rapid economic growth is not always accompanied by significant reductions in child undernutrition (Hou 2015; Subramanyam et al. 2011). A few studies have found that the impacts of growth on stunting tend to be significant but moderate (Heltberg 2009; Headey 2013). However, they focus on the impacts of economic growth on stunting changes[3].

While the scientific debate has somewhat focused on methodological aspects such as the type of modeling approach (Alderman et al. 2014), the data used (O'Connell and Smith 2016; Mary et al. 2018b), or the modeling form imposed on the relationship between stunting and GDP (Bershteyn et al. 2015[4]), little has been said about the reverse causality between economic growth and child stunting, that is, not only does growth affect stunting, but stunting also affects growth (McGovern et al. 2017). Several studies have failed to recognize this simultaneity and may have produced inconsistent estimates because of the endogeneity bias (e.g., Ruel et al. 2013; O'Connell and Smith 2016). In particular, the presumably negative reverse causality implies that OLS estimates in these studies are biased downwards, overstating the actual impact of economic growth towards child stunting reductions.

Conversely, there are a few studies that account for the reverse causality (Vollmer et al. 2014a; Smith and Haddad 2015; Mary et al. 2018b). For example, Webb and Block (2012) use System Generalized Methods of Moments estimations to account for the reverse causality, but the reliability of inference based on such estimators has been questioned (Bazzi and Clemens 2013). Indeed, there is no formal test to tackle under-identification and/or weak instrument issues in the dynamic panel data context (Mary et al. 2018b). Recently, Smith and Haddad (2015) use instrumental variables and find rather large impacts of economic growth on stunting. However, their identification strategy may not be appropriate because some instruments, though they pass Hansen's *J*-tests, are not theoretically convincing. For example, cereal yields are a direct component of agricultural value added, which is a subsector of GDP; therefore, this instrument is, by construction, endogenous. A somewhat comparable criticism can be partly extended to studies using the investment share of GDP as instrument such as Vollmer et al. (2014a) (see Acemoglu et al. 2008; Brückner and Lederman 2015)[5]. Further, Mary et al.

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[1] While we acknowledge the existence of a large microeconomic literature linking stunting to individual economic outcomes, our focus is on the aggregate costs to the economy and therefore requires discussing cross-country studies. A thorough review of the microeconomic literature can be found in McGovern et al. (2017).

[2] Smith and Haddad (2002) also suggest that economic growth has substantial impacts on reducing child underweight.

[3] This approach is often described as estimating the short run impacts of economic growth on stunting, as opposed to most of the literature that examines the long run impacts of economic growth. More fundamentally, they assume no endogeneity between stunting changes and changes in GDP per capita.

[4] Bershteyn et al. (2015) argue that most estimates in the literature reflect similar realities, concluding that a 10% increase in per capita GDP yields between a 0.7 and 2.2% decrease in stunting prevalence. However, their discussion fails to recognize that the modeling form used also embeds theoretical beliefs on whether increased GDP per capita has constant/diminishing returns towards child stunting.

[5] Interestingly, Smith and Haddad (2002) note that using the investment share of GDP and the foreign investment share of GDP as instruments they cannot reject the exogeneity of economic growth to child underweight.

(2018b) use a natural experiment based on random and exogenous variation in temperatures. However, their approach relies on assuming away any physiological effects of temperature shocks, which seems to be a strong identification assumption[6]. In sum, this discussion not only casts doubt on the empirical results found in these studies but also demonstrates the difficulty of finding plausibly exogenous instruments for economic growth.

This paper uses a novel approach[7] accounting for the reverse causal effect of stunting on GDP per capita but does not require exogenous instruments for GDP per capita. Instead, the estimation strategy identifies the causal impact of per capita GDP (in logs) on stunting by following a two-step procedure that has been used in other similar contexts where the search for valid instruments has been especially elusive (e.g., Brückner 2013; Brückner and Lederman 2015). First, we estimate the reverse causal impacts of child stunting on per capita GDP using rainfall and temperature anomalies as instrumental variables (IV) to generate exogenous variations in child stunting. In a second step, we estimate the effect that per capita GDP has on stunting using the residual per capita GDP that is not driven by stunting as an instrument. While the latter estimate is our main focus, the former is also of interest to researchers and policymakers. Estimating this reverse causal impact would provide direct evidence of the extent to which the waste of human potential severely constrains the countries' economic development.

Using a sample of 74 countries observed between 1984 and 2014, we find that current economic growth modestly reduces child stunting. A 10% increase in GDP per capita would reduce stunting prevalence by 2.7%. We also estimate the reverse causal impacts of stunting on current growth and find that a 1 percentage point increase in stunting prevalence results in a 0.4% decrease in current GDP per capita. A back-of-the-envelope calculation suggests that stunting costs on average about 13.5% of GDP per capita in developing countries. The remainder of the paper is as follows. Section 2 describes the data, the empirical model, and the identification strategy. Section 3 presents the results. Section 4 discusses the results.

2. Methodology

2.1. Data

We initially collected a dataset on child stunting and several basic determinants for a sample of 86 low-income and middle-income countries between 1984 and 2014. Given that the impact of governance must be observed over the long run, the selection of countries and years was determined by available data on governance. The Political Risk Services (PRS) dataset from the International Country Risk Guide combines a large country coverage and long-time series on multiple dimensions of governance and has been used extensively in empirical research. We gathered data for all low-income and middle-income countries and years available in the PRS dataset. We then exclude countries with less than two observations on child stunting over the period[8] and find one outlier (i.e., Iraq 1991) using leverages versus residuals plots. The final sample includes 74 countries for a total of 412 observations. Table 1 displays descriptive statistics for the dataset.

In line with most recent studies, we use stunting (height for age) as a variable for child undernutrition rather than wasting or underweight (weight for age) as the dependent variable, because it better captures the process of undernutrition in the medium run. Data for the prevalence of children under five who are stunted is taken from the World Health Organization (WHO n.d.). This is in line with previous studies (e.g., Ruel et al. 2013; Smith and Haddad 2015; Mary et al. 2018b). The main advantage of using the WHO database is that it has a larger coverage than other databases (e.g., Demographic

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6 In other words, temperature shocks do not affect child stunting other than through their effect on GDP per capita.
7 We use a cross-country setting because it has been the standard approach for such analyses; the alternative which uses a multilevel framework combining micro-and macro-data is likely to result in biases as explained earlier.
8 The three countries excluded are Cuba, Belarus, and Paraguay.

Heath Surveys—DHS) because it cumulates information from different surveys (e.g., DHS, Multiple Indicator Cluster Surveys, national health surveys). It is, however, important to note there is an important limitation to WHO data in that the country-level estimates are built from surveys based on different sampling frames and samples sizes.

The prevalence of stunting is the percentage of children under age 5 whose height for age is more than two standard deviations below the median for the international reference population ages 0–59 months. For children up to two years old, height is measured by recumbent length. For older children height is measured by stature while standing. The data is based on the child growth standards released in 2006 by the WHO. While there are other stunting variables that cover partial life range (24–36 months), most studies use the 0–59 months reference. Therefore, our decision to use this measure is driven by the need to compare with existing studies. This measure has also been frequently used in policy discussions, and has continuously attracted attention across all development stakeholders. It is also now recognized directly in the (Sustainable Development Goals Agenda, SDG 2, Goal 2.2 (Sustainable Development Goals n.d.).

Moreover, while it is widely acknowledged that the interpretation of stunting measurements is heavily dependent on the growth standards used to compare and interpret values, De Onis and Branca (2016) suggest that the prevailing international consensus is that children of all ethnic backgrounds have similar growth potential. Of course, there may be other sources of bias; for example, stunting may be under-reported because short stature is considered normal in specific communities. Another source of bias may come from reporting errors when health professionals interpret measurements (De Onis and Branca 2016). Yet, stunting data based on WHO standards have become the global harmonized reference and are considered to be an accurate description of physiological growth for children.

Table 1. Description of variables and descriptive statistics (N = 412).

Variable Name (Unit)	Mean	St. Dev.	Min	Max.
Child stunting prevalence (% Children under five)	34.12	14.36	4.30	76.70
GDP per capita (2005 international dollars)	4232	3376	415	17,452
Governance index (0–1)	0.50	0.10	0.13	0.76
Urbanization rate (% total population living in urban areas)	42.42	17.96	10.26	86.46
Temperature anomaly	0.01	0.56	−6.93	4.93
Quadratic term, Temperature anomaly	0.31	3.10	0.00	48.11
Cubic term, Temperature anomaly	−0.15	19.02	−333.70	120.27
Rainfall anomaly	0.002	0.131	−0.501	0.463

For GDP per capita, we use data from the World Bank database (World Bank 2017b). GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Data are in constant 2005 U.S. dollars (in purchasing power parity).

The PRS dataset provides 12 indicators, based on experts' analyses, to capture governance in its different characteristics, covering both political and social attributes. We use an index of governance which is similar to the one used in Smith and Haddad (2015), combining the following: Bureaucratic Quality, that is, the institutional strength and quality of the bureaucracy; Law and Order, that is, the strength and impartiality of the legal system and popular observance of the law; Government Stability, that is, the government's ability to carry out its declared programs and associated policies, and its ability to stay in office; Corruption within the political system, that is, the threat to foreign investment by distorting the economic and financial environment, reducing the efficiency of government and business by enabling people to assume positions of power through patronage rather than ability, and introducing inherent instability into the political process; and Democratic Accountability, that is, a measure of how responsive government is to its people, on the basis that the less responsive it is, the more likely it is that the government will fall, peacefully in a democratic society, but potentially violently in a non-democratic one (PRS 2016).

The index is the simple mean of these five indicators for each country-year data point after placing each on a 0–1 scale so that they have equivalent ranges and weights. Each dimension of governance above can directly or indirectly promote reductions in child stunting. For example, bureaucratic effectiveness and political stability directly contribute to the quality and reliability of the provision of nutrition and social services which support many children's nutritional status. Similarly, democratic accountability ensures that pressures are maintained for public action because increased awareness of the importance of nutrition is likely to encourage governments to be more responsive to the needs of food-insecure people, especially children.

Rainfall and temperature data is from the Climate Research Unit (CRU) and the Tyndall Centre for Climate Change Research (TYN) of the University of East Anglia, from the dataset is CRU TS v. 3.23. The gridded climate dataset (referred to as CRU TS3.10) is built from monthly observations at meteorological stations across the world's land areas, interpolated into 0.5° latitude/longitude grid cells covering the global land surface (excluding Antarctica), and combined with an existing climatology to obtain absolute monthly values (Harris et al. 2014). We also include the urbanization rate, as well as the proportion of the countries' populations that are 15–64 years old, the proportion that are 65 or older and trade openness. All variables are taken from the World Development Indicators (WDI) that can be found at http://databank.worldbank.org/data/source/world-development-indicators#.

2.2. Model and Identification Strategy

The empirical model can be expressed as follows:

$$S_{it} = \beta \ln(GDP_{it}) + \gamma gov_{it} + \alpha URB_{it} + c_i + d_t + \mu_{it} \tag{1}$$

where country is indexed by i and year is indexed by t; S_{it} is the prevalence of child stunting of country i in year t; GDP_{it} is GDP per capita (in purchasing power parity); gov_{it} is a composite index of governance and URB_{it} is the urbanization rate; c_i is a country-specific effect; and d_t is time fixed effect. μ_{it} is an error term. The modeling specification implies that economic growth has diminishing marginal returns towards stunting reductions in line with previous studies. β is the key coefficient of interest as it displays the effect of economic growth on child stunting. The inclusion of country fixed effects accounts for the existence of time invariant omitted variables, while the inclusion of time fixed effects controls for the presence of common shocks affecting both stunting and economic growth.

The literature has often used in parsimonious models with no or few independent variables (e.g., Ruel et al. 2013; Headey 2013; Heltberg 2009) mainly to avoid losing stunting observations (that are already limited). In line with the literature, we keep our model parsimonious and only account for the role of governance and urbanization. The inclusion of these variables is guided by the desire to include only basic determinants of undernutrition (UNICEF 1998) and to follow the existing literature (e.g., Smith and Haddad 2015; Mary et al. 2018b). We also test a more extended version of this model in robustness analyses.

Following Smith and Haddad (2015), governance is defined as the set of traditions, policies, and institutions (and implicitly their effectiveness) that work towards ensuring food security, primarily for children. Improved governance may reduce stunting because the quality and reliability of the provision of nutrition and social services, which support many children's nutritional status, will improve with stronger institutions. For example, governments may be more likely to honor human rights, especially the rights to food and nutrition (Smith and Haddad 2000). Furthermore, the provision of basic services that impact household food and nutrition security, such as adequate housing, water, and sanitation systems, as well as provision of health clinics and schools, is of better quality and more stable in urban areas than in rural areas, therefore incentivizing a movement from rural populations towards urban areas.

As explained in the introduction, finding a strategy to account for reverse causality can be problematic. To avoid the difficult search for valid instruments for GDP per capita, we adapt the approach devised by Brückner (2013)[9]. As a first step, we estimate the effect that stunting has on per capita GDP, using an instrumental variable (IV) approach. Equation (2) presents the first-step estimation:

$$\ln(GDP_{it}) = \omega S_{it} + \pi gov_{it} + \delta URB_{it} + \rho_i + g_t + \tau_{it} \qquad (2)$$

ρ_i are country fixed effects. g_t are time fixed effects. τ_{it} is an error term.

The statistical significance of ω provides a direct endogeneity test of stunting. Estimating the effect that stunting has on GDP per capita requires an exogenous source of variation for stunting. Therefore, rainfall and temperature anomalies, defined here as deviations from the long run mean calculated over the full sample period, (and higher moments) are used as excluded instruments in the two-stage least squares (2SLS) estimation of Equation (2). Weather anomalies (z) are generally defined as follows:

$$z_{it} = \frac{a_{it} - \overline{a_i}}{\overline{a_i}}$$

where $\overline{a_i}$ is the mean temperature (rainfall) level, observed over the full time period, in country i; a_{it} is the temperature (rainfall) level in year t. If z_{it} is positive (negative), this indicates that the average temperature (rainfall) in year t in country i is above (below) the long run level. Higher moments of z capture potentially nonlinear effects. The first stage estimation of Equation (2) can be summarized:

$$S_{it} = aT_{it} + bT_{it}^2 + cT_{it}^3 + dR_{it} + X_i + Z_t + l_{it}$$

where T_{it} is the temperature anomaly; R_{it} is the rainfall anomaly; X_i are country specific fixed effects; Z_t are year dummies; l_{it} is an error term.

In a second step, we construct an adjusted per capita GDP series, $\ln(GDP^*_{it})$, where the response of per capita GDP to stunting (ωS_{it}) is 'partialled out' using estimates from Equation (2):

$$\ln(GDP^*_{it}) = \ln(GDP_{it}) - \omega S_{it} - \pi gov_{it} - \delta URB_{it}$$

$\ln(GDP^*_{it})$ is free of the endogeneity bias and is used to instrument $\ln(GDP_{it})$ in estimating Equation (1) via 2SLS. The second-step estimation is exactly identified. Instruments are also included as independent variables in the second-step estimation.

The approach is particularly appealing because it identifies the causal effect of economic growth on child stunting, while also estimating the reverse causal effect of stunting on economic growth. This implicitly allows proving the presence (or absence) of endogeneity in the estimation of Equation (2). In line with Smith and Haddad (2015) and Mary et al. (2018a), other independent variables are assumed exogenous.

Because weak instruments may affect the first step and make the 2SLS inconsistent, we use the Continuous Updating Estimator (CUE) estimator when appropriate. CUE has also been found to perform better than Limited Information Maximum Likelihood, 2SLS, or bias-corrected Generalized Method of Moments estimators in the case of weak instruments (Donald et al. 2009; Davies et al. 2014).

What makes this identification strategy plausible? First, temperature or rainfall anomalies are exogenous and random. Second, weather shocks affect the physiology of children (for a recent literature review, see Gao et al. 2014) and therefore are likely correlated with stunting

9 The theoretical proof on the validity of his approach can easily be adapted to our framework.

prevalences (Millward 2017). For example, higher temperatures than usual may lead to an expansion of vector-borne diseases (Rabassa et al. 2014). Children are also more vulnerable to temperature because of a higher body surface area-to-mass ratio, a higher metabolic rate, and a likely longer exposure to heatwaves because of a lower awareness of their effects (Garcia and Sheehan 2016). Third, stunting is not fully determined within the first two years of a life. Stunting has been portrayed as a chronic condition because of growth faltering (that is, height-for-age of children observed later in life is, to some degree, a reflection of failure to grow before age 2). However, there is an intense ongoing debate on whether substantial height catch-up can occur between 24 months and mid-childhood, even in the absence of any interventions (Prentice et al. 2013b; Prentice et al. 2013a; Prendergast and Humphrey 2014; Leroy et al. 2013). In a seminal paper, Prentice et al. (2013a) show that a pubertal growth phase in rural Gambian children allows very considerable height recovery and conclude that their data are sufficient to dispel the myth of life-long size entrainment by age 24 months (Prentice et al. 2013a). The main important takeaway from this debate is that stunting is not a static phenomenon.

The main identifying assumption for our identification strategy is that current weather anomalies are physiological shocks that affect stunting, and hence GDP per capita[10]. Traditionally, the effects of stunting, mainly through lower physical and cognitive capacities, can be seen as a negative productivity shock, resulting in lower growth. What about the exclusion restriction for the estimation of Equation (2)? It is important to note that the exclusion restriction might be problematic because current weather anomalies may affect current economic growth. Indeed, higher temperature (rainfall) than usual may result in lower (higher) agricultural output and hence lower (higher) GDP. The use of weather anomalies for instruments, however, weakens the case for large effects. This is, for example, because dryer or warmer weather than usual would unlikely change the already affected economy in any sizeable way. This is especially true as there are few very large-scale temperature shocks in our sample; 90% of temperature anomalies represent variations from long-run levels between −2.4% and 4%. The case of rainfall shocks[11] is more complex as it depends on multiple factors such as seasonality, timing of rainfall anomalies, or crop cycle. However, while excess rainfall will certainly affect agricultural output, its effect is likely to take place with some delay (Rabassa et al. 2014). Moreover, it is also important to stress that growing seasons may overlap calendar years in many developing countries (Vrieling et al. 2013), therefore possibly postponing most of the income effect of rainfall shocks to the following year. This is line with microeconomic studies that have shown that past weather shocks affect current farm production (e.g., Salazar-Espinoza et al. 2015; Rabassa et al. 2014). Moreover, rainfall variations can affect economic growth through other channels such as schooling (Maccini and Yang 2009). The validity of the exclusion restrictions with respect to using rainfall anomalies in the IV estimation of Equation (2) therefore relies on the size of these potential effects.

In line with Brückner (2013), we provide supportive evidence that weather anomalies have no large effects on current economic growth other than through stunting via a set of additional regressions in which instruments are added as right-hand-side variables to Equation (2). Additionally, the Hansen's *J*-test of over-identification of all instruments is used to investigate the validity of our instruments. This tests the null hypothesis that the instruments are uncorrelated with the error term. If the *p*-value is below 10%, we can conclude that all instruments are not exogenous and therefore invalid. The strength of instruments is further examined by reporting the Kleibergen-Paap rk Wald *F* statistic (or *F*-statistic) that we compare with the critical values from Stock and Yogo (2005) for testing weak instruments. We test the null hypothesis that the maximum relative bias and size distortions are greater than 10%, 15%, or 20%.

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[10] Given the high incidence of child labour in developing countries, there is also a direct negative effect of stunting on current GDP per capita because some of the children surveyed who are almost five or four may already be working. For example, it is estimated that more than one in five children in Africa are employed against their will in stone quarries, farms, and mines (International Labour Organization ILO).

[11] By contrast, large-scale rainfall shocks are much more common in our sample as 90% of rainfall shocks represent variations from long-run levels between −20.5% and 22.5%.

There is a more fundamental way to lessen the concerns relative to the exclusion restrictions. Mary et al. (2018b) argue that previous studies should have looked at the impacts of current and previous economic growth on stunting because an observation on stunting prevalence in 2000 may have been partially caused by economic growth determined as early as in 1995. To account for this, they use a modeling framework using 5-year rolling averages of regressors. If we adopt a similar framework, the exclusion restrictions become valid by design. Indeed, it would be impossible for current weather anomalies to affect a variable that now mainly represents previous economic growth. Equation (1) can be rewritten:

$$S_{it} = \vartheta \ln(GDP_{it}^{MA5}) + \varphi gov_{it}^{MA5} + \sigma URB_{it}^{MA5} + v_i + f_t + \epsilon_{it} \quad (3)$$

where the superscript MA5 denotes the 5-year moving average of the regressors. For example, the 5-year moving average of economic growth is calculated as follows:

$$\ln(GDP_{it}^{MA5}) = \frac{\ln(GDP_{it}) + \ln(GDP_{it-1}) + \ln(GDP_{it-2}) + \ln(GDP_{it-3}) + \ln(GDP_{it-4})}{5}.$$

We therefore estimate Equation (3) using the two-step approach described above as a robustness check to our identification strategy. It is important to recognize, however, that this represents a change in the structural model as ϑ captures the average effect of economic growth of the last five years on the prevalence of stunting.

3. Results

This paper examines the relationship between economic growth and the prevalence of child stunting. We use country-clustered standard errors that are robust to heteroscedasticity. Table 2 presents the estimates for the effect that child stunting has on current GDP per capita and demonstrate that GDP per capita is indeed endogenous to child stunting. The first-stage estimates that link rainfall and temperature anomalies (and higher moments) to child stunting are displayed in Table 2, Column 1. Increased rainfall levels from their long run averages are associated with decreased stunting prevalence. Coefficients for the higher moments of the temperature shock capture the fact that the relationship between temperature and stunting is nonlinear. In particular, small-scale (large-scale) positive temperature shocks decrease (increase) stunting prevalence.

3.1. Effect of Child Stunting on GDP Per Capita

The 2SLS estimate in Column 2 of Table 2 suggests that a percentage point increase in child stunting prevalence decreases current GDP per capita by 0.2%. From a methodological standpoint, the presence of negative reverse causality implies that OLS estimates would be biased downwards, overstating the negative impact of current economic growth on stunting. Overall, instruments yield a first-stage F-statistic (or Kleibergeen-Paap statistic) that is just above 10, just a little below the 10% relative bias Stock-Yogo value (10.27). However, the F-statistic is also below the 20% maximal IV size Stock Yogo value, indicating weak instruments.

When we re-estimate Equation (2) with CUE[12], we find the stunting coefficient is negative and significant at 5%, implying that a percentage point increase in child stunting prevalence decreases current GDP per capita by 0.4%. A back-of-the-envelope calculation suggests that stunting costs on average about 13.5% of GDP per capita in developing countries[13]. There are few relevant estimates in the literature but our estimate is within the range of existing similar estimates found in IFPRI (2014), though somewhat higher than those in in World Bank (2017a). This can be partly explained by the

12 Note that the maximum relative bias is zero for the CUE estimator.
13 We simply multiply 0.4 by the average stunting rate.

fact that the latter study uses a development accounting approach and ignores potentially important externalities and spillover effects (World Bank 2017a).

We have discussed the exclusion restriction in the modeling section. First, the *p*-values of the Hansen *J*-test on the over-identifying restrictions in Table 2 are greater than 10% in all columns. Hence, the tests do not reject that the instruments are uncorrelated with the second-stage error. Second, we also provide additional estimations to examine intuitively whether weather anomalies have large effects on economic growth, other than through stunting. Columns 4–6 add rainfall and temperature anomalies as right-hand-side variables to Equation (2). The coefficients associated with the instruments in those columns are statistically insignificant. These results seem to support the result of the Hansen *J* test and suggest the validity of the exclusion restrictions.

3.2. Effect of GDP Per Capita on Child Stunting Prevalence

Table 3 shows estimates of the effect of GDP per capita on child stunting. All coefficients associated to economic growth are negative and significant at 1%. Column 1 reports the OLS estimation results of Equation (1), which looks at the impact of current economic growth on stunting. Results suggest that a 10% increase in GDP per capita results in a 3.6% decrease in child stunting prevalence[14]. When we account for endogeneity, the coefficients in Columns 2 and 3 imply smaller impacts. This is line with the negative reverse causality estimated in Table 2.

Table 2. The effect of stunting on economic growth.

	First Stage	**2SLS-IV**	**CUE**	**2SLS-IV**	**2SLS-IV**	**2SLS-IV**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent variable	*Stunting*	Growth	Growth	Growth	Growth	Growth
Child stunting prevalence		−0.002 **	−0.004 **	−0.016 **	−0.002 **	−0.018 *
		[0.02]	[0.02]	[0.02]	[0.02]	[0.06]
Governance index		0.393	0.367 **	0.160	0.382	0.135
		(1.29)	(2.24)	(0.85)	(1.23)	(0.70)
Urbanization		0.023	0.007	0.016	0.023	0.015
		(1.28)	(0.83)	(1.12)	(1.29)	(1.11)
Rainfall anomaly	−2.642 #			−0.092		−0.096
	(−1.43)			(−1.32)		(−1.39)
Temperature anomaly	−2.143 ***				0.007	0.008
	(−4.03)				(1.03)	(1.38)
Temperature anomaly, squared	0.122 #					
	(1.60)					
Temperature anomaly, cubic	0.074 ***					
	(4.14)					
Observations	412	412	412	412	412	412
Number of countries	74	74	74	74	74	74
Country fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Hansen *J*, *p*-value	n.a.	0.56	0.28	0.56	0.56	0.56
First-stage *F*-stat	n.a.	10.21	10.21	11.91	13.61	17.83
Stock-Yogo 10% size	n.a.	24.58	5.44	24.58	24.58	24.58
Stock-Yogo 20% size	n.a.	10.26	3.30	10.26	10.26	10.26
Stock-Yogo 10% relative bias	n.a.	10.27	n.a.	10.27	10.27	10.27
Stock-Yogo 20% relative bias	n.a.	6.71	n.a.	6.71	6.71	6.71

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant (p-value < 0.15). Robust country-clustered z-statistics in parentheses. Anderson-Rubin p-values in square brackets.

Especially the coefficient in Column 3 based on the CUE estimate in Table 2, our preferred estimate (given that weak instruments affect the 2SLS estimate in Table 2), suggests that a 10% increase in GDP per capita results in a 2.7% decrease in child stunting prevalence[15]. This estimate is well below the

[14] This is calculated as $\frac{12.378}{34.12} * \frac{10}{100} \approx 3.6\%$.
[15] This is calculated as $\frac{9.143}{34.12} * \frac{10}{100} \approx 2.7\%$.

range found in similar relevant studies (e.g., Ruel et al. 2013; Smith and Haddad 2015; Mary et al. 2018b; Mary et al. 2018a), but much higher than those found in Vollmer et al. (2014a).

It is important to stress that the latter is fundamentally different from our paper because of the multi-level methodology as well as the limited country coverage. This finding provides modest support for pro-poor growth but cast doubt on the idea that economic growth is a sufficient condition for child undernutrition reductions. This implies that child stunting reductions cannot solely rely on income growth but also requires direct nutritional investments.

Furthermore, we find that improved governance reduces stunting as all associated coefficients are negative and statistically significant. This suggests that the quality of policies and institutions is a critical element for directly ensuring food and nutrition security. This result is virtually identical to those in Smith and Haddad (2015) and Mary et al. (2018b). Additionally, urbanization is found to have a negative effect on stunting, though the effect is imprecisely estimated in Column 1. The Ramsey RESET tests somewhat indicate that an appropriate functional form has been used, and omitted variable bias is not likely a problem[16] in the estimations as *p*-values are (barely) above the 5% level in all columns.

Table 3. The effect of economic growth on child stunting.

	OLS-FE	**2SLS-IV**	**2SLS-IV**
Child stunting prevalence	(1)	(2)	(3)
Economic growth (Ln GDP per capita)	−12.378 ***	−10.957 ***	−9.143 ***
	(−5.50)	(−5.07)	(−4.34)
Urbanization rate	−0.202 #	−0.236 *	−0.280 **
	(−1.51)	(−1.79)	(−2.12)
Governance index	−10.548*	−11.139 **	−11.893 **
	(−1.94)	(−2.01)	(−2.07)
Rainfall anomaly		−3.175 *	−3.087 *
		(−1.95)	(−1.90)
Temperature anomaly		−1.681 ***	−1.757 ***
		(−4.21)	(−4.32)
Temperature anomaly, squared		0.108 **	0.111 **
		(2.02)	(2.00)
Temperature anomaly, cubic		0.061 ***	0.063 ***
		(4.20)	(4.30)
Observations	412	412	412
Number of countries	74	74	74
Ramsey RESET test	0.06	0.05	0.05
First-stage F stat	n.a.	55,356	11,477

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant (p-value < 0.15). Robust country-clustered z-statistics in parentheses.

3.3. Alternative Model Using 5-Year Moving Averages

As explained earlier in the modeling section, the validity of the exclusion restrictions in the IV estimation of Equation (2) determines the causality of our claims in this paper. While we have provided supportive evidence in favor of those restrictions in Table 2, we can reproduce the analysis using the variant in Equation (3) where regressors are expressed as 5-year moving averages, as main model. The key advantage of this specification is that the exclusion restrictions hold by design. The main issue is that we cannot compare these estimation results directly with those in Table 3 because Equation (3)

[16] We use Ramsey RESET tests, based on GMM distance following Hashem Pesaran and Taylor (1999)'s guidance.

presents a different structural model. Nonetheless, if results were to be somewhat similar (despite being based on a slightly different sample), it would provide reassuring evidence in favor of the exclusion restrictions in our previous analysis.

The 2SLS estimate in Column 1 of Table A2 suggests that a percentage point increase in child stunting prevalence decreases GDP per capita by 0.4%. This estimate is similar to the one in Table 2. Again, the reverse causality is negative implying that the OLS estimate in Table 4 would be biased downwards. Indeed, the 2SLS coefficient in Column 2 of Table 4 is smaller in absolute values to that of Column 1. In particular, the 2SLS estimate is negative and statistically significant at 1% and suggests that a 10% increase in GDP per capita results in a 2.4% decrease in child stunting prevalence on average two years later[17] (as opposed to a 3.5% reduction in stunting prevalence according to the OLS estimate).

Table 4. The effect of economic growth on stunting prevalence.

	OLS-FE	**2SLS-IV**
Child stunting prevalence	(1)	(2)
Economic growth	−11.771 *** (−4.23)	−8.047 *** (−3.03)
Urbanization rate	−0.314 ** (−2.21)	−0.406 *** (−2.92)
Governance index	−18.185 *** (−2.83)	−19.708 *** (−2.94)
Rainfall anomaly		−3.739 ** (−2.15)
Temperature anomaly		−1.947 *** (−4.48)
Temperature anomaly, squared		0.092 # (1.64)
Temperature anomaly, cubic		0.067 *** (4.15)
Observations	392	392
Number of countries	74	74
Ramsey RESET test	0.05	0.08
First-stage *F* stat	n.a.	7617

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant (p-value < 0.15). Robust country-clustered z-statistics in parentheses.

3.4. Robustness Analyses

Last, we investigate the robustness of our empirical results to (1) the inclusion of outliers, (2) the exclusion of year dummies, (3) the exclusion of India which is the country with the highest number of stunted children in the world, (4) the exclusion of Bangladesh which is the country with the highest number of stunting observations in the sample, (5) the use of an extended model, and (6) a basic model with any independent variables. The extended model includes trade openness (exports plus imports divided by GDP) extracted from the WDI and a measure of the military's involvement in politics from the PRS dataset. Trade might affect children's health through a number of pathways, including the degree to which governments are willing and able to fund public health, higher access to clean water, or health care (Levine and Rothman 2006). Military involvement might stem from an external or

[17] This is calculated at the midpoint of the moving average.

internal threat, be symptomatic of underlying difficulties, or be a full-scale military takeover. They may control food supply or use it as a weapon or payment for political support, therefore disrupting its distribution towards the populations that need food the most. The model without independent variables matches the model used in previous studies and allows a direct comparison.

Estimation tables can be found in the Appendix A. The overall message is that the main pattern of results remains the same. In short, the range of estimates in Table A4 (A6) suggests that a 10% increase in GDP per capita would result in a 2.1–3.1 (1.4–2.6)% decrease in child stunting prevalence. We also present results that rely on using the prevalence of underweight as a dependent variable in Table A7. Table A7 suggests that a 10% increase in GDP per capita results in a 1.9% decrease in child underweight prevalence. Additionally, a percentage point increase in child underweight prevalence decreases current GDP per capita by a little less than 0.1%.

4. Discussion

The question of how to fight child undernutrition is high on the agenda, as the SDG timeline has taken for objective to end all forms of malnutrition by 2030. Within that context, the role of economic growth, which is often considered to be central for development strategies, has recently been the target of increased scientific scrutiny. While it is generally accepted that economic growth decreases child undernutrition, the empirical evidence has been quite contrasted, primarily in regard to the magnitude of the impacts.

This paper estimates the impacts of increases in current GDP per capita on the prevalence of child stunting in developing countries using a novel approach to account for the reverse causal effect of stunting on GDP per capita. Our findings show that a 10% increase in GDP per capita reduces child stunting prevalence by 2.7%. A sensitivity analysis confirms that the amplitude of the estimated effects is somewhat robust across alternative specifications.

We also estimate the reverse causal impacts of stunting on GDP per capita. In particular, we find that a percentage point increase in child stunting prevalence results in a 0.4% decrease in current GDP per capita. A back-of-the-envelope calculation suggests that stunting costs on average about 13.5% of GDP per capita in developing countries.

Our findings suggest that economic growth is modestly pro-poor in our sample but cast doubt on the idea that economic growth is a sufficient condition for child undernutrition reductions. This implies that child stunting reductions cannot solely rely on income growth but also requires direct nutritional investments. This conclusion seems to be a converging point in the literature (McGovern et al. 2017). Yet, given the proven effectiveness of nutrition-specific and nutrition-sensitive interventions (e.g., Bhutta et al. 2008; Mary et al. 2018a), our results may influence how policy makers prioritize their limited financial resources between supporting pro-poor growth investments and direct nutritional interventions.

A few caveats need be mentioned. First, while we believe the approach may be used in other development settings, it is also restrictive in terms of the identification assumptions. We recommend that further analyses present empirical support for these assumptions, or at least provide additional robustness analyses (as we have done so in this paper). Second, it is not possible to apply this approach at the regional level because of the lack of stunting data. We therefore are not able to produce estimates individually for Sub-Saharan Africa, South East Asia, and Latin America. Last, further research could investigate the type of economic growth that can be better leveraged for reducing stunting in line with a few studies which examine the role of agricultural growth versus non-agricultural growth.

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Appendix A

Table A1. List of countries (by alphabetical order).

Albania; Algeria; Angola; Armenia; Azerbaijan;
Bangladesh; Bolivia; Botswana Brazil; Burkina Faso;
Cameroon; China; Colombia; Congo, DR; Congo, REP; Costa Rica; Cote d'Ivoire;
Dominican Republic;
Ecuador; Egypt; El Salvador; Ethiopia;
Gabon; Gambia; Ghana; Guatemala; Guinea; Guinea-Bissau; Guyana;
Haiti; Honduras;
India; Indonesia; Iran; Iraq;
Jordan;
Kazakhstan; Kenya;
Lebanon; Liberia;
Madagascar; Malawi; Mali; Mexico; Moldova; Mongolia; Morocco; Mozambique;
Namibia; Nicaragua; Niger; Nigeria;
Pakistan; Panama; Papua New Guinea; Peru; Philippines;
Romania;
Senegal; Sierra Leone; South Africa; Sri Lanka; Sudan;
Tanzania; Thailand; Togo; Tunisia; Turkey;
Uganda; Ukraine;
Vietnam;
Yemen;
Zambia; Zimbabwe.

Table A2. The effect of stunting on economic growth: using 5-year moving averages.

	First Stage	**2SLS-IV**	**2SLS-IV**	**2SLS-IV**	**2SLS-IV**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent variable	*Stunting*	Growth	Growth	Growth	Growth
Child stunting prevalence		−0.004 **	−0.018 **	−0.004 **	−0.018 ***
		[0.03]	[0.02]	[0.03]	[0.01]
Governance index		0.316	0.004	0.314	−0.003
		(0.98)	(0.02)	(0.97)	(−0.02)
Urbanization		0.023	0.014	0.022	0.014
		(1.40)	(1.09)	(1.40)	(1.09)
Rainfall anomaly	−3.411 *		−0.097		−0.098
	(−1.78)		(−1.27)		(−1.30)
Temperature anomaly	−2.469 ***			0.002	0.003
	(−5.19)			(035)	(0.55)
Temperature anomaly, squared	0.145 **				
	(2.12)				
Temperature anomaly, cubic	0.084 ***				
	(5.08)				
Observations	392	392	392	392	392
Number of countries	74	74	74	74	74
Country fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Hansen J, p-value	n.a.	0.56	0.60	0.33	0.31
First-stage F-stat	n.a.	15.23	15.42	19.35	22.11
Stock-Yogo 10% size	n.a.	24.58	24.58	24.58	24.58
Stock-Yogo 20% size	n.a.	10.26	10.26	10.26	10.26
Stock-Yogo 10% relative bias	n.a.	10.27	10.27	10.27	10.27
Stock-Yogo 20% relative bias	n.a.	6.71	6.71	6.71	6.71

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant. Robust country-clustered z-statistics in parentheses. Anderson-Rubin p-values in square brackets.

Table A3. The effect of stunting on economic growth: robustness analyses.

	CUE	CUE	CUE	CUE	2SLS-IV	2SLS-IV
	(1)	(2)	(3)	(4)	(5)	(6)
Growth	*Outliers*	*No year dummies*	*No India*	*No Bangladesh*	*Extended model*	*Basic model*
Child stunting prevalence	−0.002 ** [0.02]	−0.004 *** [0.00]	−0.003 ** [0.03]	−0.007 ** [0.03]	−0.003 *** [0.00]	−0.009 *** [0.00]
Urbanization	0.021 (1.13)	0.032 *** (3.57)	0.008 (0.96)	0.004 (0.47)	0.022 (1.28)	
Governance index	0.417 # (1.37)	0.450 *** (2.86)	0.355 ** (2.13)	0.346 ** (2.03)	0.146 (0.56)	
Observations	412	412	406	391	404	417
Number of countries	74	74	73	73	72	74
Country fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	NO	YES	YES	YES	YES
Hansen J, p-value	0.52	0.56	0.60	0.33	0.55	0.47
First-stage F-stat	10.13	15.23	15.42	19.35	13.83	16.59
Stock-Yogo 10% size	5.44	5.44	5.44	5.44	24.58	24.58
Stock-Yogo 20% size	3.30	3.30	3.30	3.30	10.26	10.26
Stock-Yogo 10% relative bias	n.a.	n.a.	n.a.	n.a.	10.27	10.27
Stock-Yogo 20% relative bias	n.a.	n.a.	n.a.	n.a.	6.71	6.71

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant. Robust country-clustered z-statistics in parentheses. Anderson-Rubin p-values in square brackets.

Table A4. The effect of economic growth on child stunting: robustness analyses.

	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV
	(1)	(2)	(3)	(4)	(5)	(6)
Child stunting prevalence	*No outliers*	*No year dummies*	*No India*	*No Bangladesh*	*Extended model*	*Basic model*
Economic growth	−9.661 *** (−4.52)	−10.232 *** (−4.46)	−9.675 *** (−4.49)	−7.240 *** (−3.36)	−10.678 *** (−5.37)	−7.073 ** (−2.47)
Urbanization rate	−0.303 ** (−2.20)	−0.562 *** (−4.63)	−0.270 ** (−2.03)	−0.271 ** (−2.20)	−0.192 (−1.43)	
Governance index	−11.212 * (−1.94)	−11.423 *** (−2.62)	−11.428 ** (−1.98)	−7.687 # (−1.54)	−12.537 ** (−2.04)	
Trade openness					−0.037 (−1.24)	
Military in Politics					0.235 (0.64)	
Rainfall anomaly	−3.128 * (−1.88)	−3.378 * (−1.90)	−3.109 * (−1.90)	−3.240 ** (−1.97)	−2.747# (−1.64)	−2.231 (−1.22)
Temperature anomaly	−1.721 *** (−4.27)	−1.470 *** (−4.13)	−1.708 *** (−4.17)	−1.923 *** (−4.51)	−1.839 *** (−5.04)	−2.003 *** (−4.89)
Temperature anomaly, squared	0.110 ** (2.04)	0.061 * (1.83)	0.110 * (1.92)	0.113 * (1.86)	0.137 ** (2.37)	0.120 ** (2.02)
Temperature anomaly, cubic	0.062 *** (4.23)	0.047 *** (3.99)	0.062 *** (4.14)	0.068 *** (4.39)	0.069 *** (5.12)	0.072 *** (4.98)
Observations	413	412	406	391	404	417
Number of countries	74	74	73	73	72	74
Ramsey RESET test	0.07	0.04	0.07	0.26	0.09	0.03
First-stage F-stat	37,955	55,356	16,934	3,936	31,750	1208

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant. Robust country-clustered z-statistics in parentheses.

Table A5. The effect of stunting on economic growth: robustness analyses using 5-year moving averages.

	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV
	(1)	(2)	(3)	(4)	(5)	(6)
Growth	*Outliers*	*No year dummies*	*No India*	*No Bangladesh*	*Extended model*	*Basic model*
Child stunting prevalence	−0.004 **	−0.007 ***	−0.003 **	−0.004 **	−0.003 **	−0.008 ***
	[0.04]	[0.00]	[0.04]	[0.03]	[0.03]	[0.00]
Urbanization	0.021 #	0.029*	0.024 #	0.023 #	0.021 #	
	−1.32	(1.70)	(1.42)	(1.43)	(1.42)	
Governance index	0.278	0.192	0.312	0.327	0.167	
	−0.86	(0.50)	(0.95)	(1.15)	(0.55)	
Observations	393	392	386	372	388	395
Number of countries	74	74	73	73	73	74
Country fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	NO	YES	YES	YES	YES
Hansen J, *p*-value	0.52	0.54	0.57	0.55	0.47	0.59
First-stage F-stat	15.25	17.38	15.42	19.35	22.91	15.57
Stock-Yogo 10% size	24.58	24.58	24.58	24.58	24.58	24.58
Stock-Yogo 20% size	10.26	10.26	10.26	10.26	10.26	10.26
Stock-Yogo 10% relative bias	10.27	10.27	10.27	10.27	10.27	10.27
Stock-Yogo 20% relative bias	6.71	6.71	6.71	6.71	6.71	6.71

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant. Robust country-clustered *z*-statistics in parentheses. Anderson-Rubin *p*-values in square brackets.

Table A6. The effect of economic growth on child stunting: robustness analyses using 5-year moving averages.

	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV	2SLS-IV
	(1)	(2)	(3)	(4)	(5)	(6)
Child stunting prevalence	*No outliers*	*No year dummies*	*No India*	*No Bangladesh*	*Extended model*	*Basic model*
Economic growth	−7.908 ***	−4.827 *	−8.596 ***	−8.422 ***	−8.625 ***	−5.045 *
	(−3.03)	(−1.92)	(−3.09)	(−3.07)	(−4.27)	(−1.65)
Urbanization rate	−0.421 ***	−0.772 ***	−0.396 ***	−0.339 ***	−0.315 **	
	(−3.11)	(−6.74)	(−2.84)	(−2.68)	(−2.26)	
Governance index	−20.103 ***	−20.801 ***	−19.450 ***	−12.762 ***	−20.942 ***	
	(−3.01)	(−3.84)	(−2.92)	(−3.09)	(−2.92)	
Trade openness					−0.072 *	
					(−1.89)	
Military in Politics					0.423	
					(1.06)	
Rainfall anomaly	−3.741 **	−3.926 **	−3.670 **	−4.040 **	−3.785 **	−2.673 #
	(−2.13)	(−2.04)	(−2.09)	(−2.29)	(−2.16)	(−1.44)
Temperature anomaly	−1.958 ***	−1.643 ***	−1.874 ***	−1.851 ***	−2.196 ***	−1.930 ***
	(−4.51)	(−5.03)	(−4.27)	(−4.29)	(−5.50)	(−4.54)
Temperature anomaly, squared	0.094 *	0.049 #	0.089 #	0.080	0.122 **	0.082
	(−1.66)	(1.49)	(1.53)	(1.34)	(2.08)	(1.36)
Temperature anomaly, cubic	0.067 ***	0.052 ***	0.065 ***	0.064 ***	0.076 ***	0.068 ***
	(−4.16)	(4.55)	(3.94)	(3.90)	(5.26)	(4.42)
Observations	393	392	386	372	388	395
Number of countries	74	74	73	73	73	74
Ramsey RESET test	0.05	0.07	0.07	0.26	0.02	0.18
First-stage *F*-stat	7959	2662	11,542	8198	18,109	1104

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant. Robust country-clustered *z*-statistics in parentheses.

Table A7. The effect of economic growth on child underweight (second step).

	(1)	**(2)**
Dependent variable	OLS−FE Underweight	CUE Underweight
Economic growth	−7.185 *** (−3.47)	−3.443 ** (−1.99)
Urbanization	−0.143 (−1.43)	−0.229 ** (−2.28)
Governance index	−11.844 ** (−2.01)	−13.643 ** (−2.16)
Temperature anomaly, squared		−0.146 *** (−3.51)
Temperature anomaly		1.265 *** (3.02)
Temperature anomaly, cubic		−0.045 *** (−3.17)
Rainfall anomaly		−2.369 * (−1.92)
Observations	438	438
Number of countries	67	67
First-stage *F*-stat	n.a.	3402

Notes: *, **, ***: significant at 10%, 5%, and 1%. #: marginally insignificant. Robust country-clustered *z*-statistics in parentheses.

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