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Commodity market instability and asymmetries in developing countries:

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Les asymétries et l'instabilité du marché des matières premières dans les

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Food prices and household welfare: A pseudo panel approach

By

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Abstract

The last years have seen an extra-ordinary surge in food prices and volatility. The academic literature on its consequences currently focuses on the effect of high food prices in specific regional and time contexts. This paper contributes to this literature in two ways: First, the analysis attempts to decompose the effect of global food prices on household welfare – i.e. is the effect driven by the trend, fluctuation around a trend, volatility or episodes of sustained price increases/decreases? Second, the paper extends the geographical and time perspective on this issue and attempts to provide a worldwide picture of the impact of the recent surge in food prices. By taking a pseudo panel approach to this topic, this paper can make use of a large amount of household information which is available from repeated cross sections of the Demographic and Health Surveys (DHS). The data subject to this analysis contain information on about 500,000 individuals from 38 countries over a period of 20 years. Instead of following individuals over time as in a standard panel set-up, cohorts are followed over time. To remedy bias from measurement error in the context of the pseudo panel, the Verbeek-Nijman (1992) estimator, a variant of Deaton (1985)'s errors-in-variables model, is applied. The empirical analysis shows that adverse effects of food prices on household welfare are transmitted through both short term-fluctuation in prices (volatility, period-to-period changes) as well as permanent price shocks (trend, episodes of sustained price increases). There is mixed evidence on the impact of short-term fluctuations around a trend and periods of sustained drops in prices.

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1 Introduction

The last decade has seen a stark increase in world food prices and food price volatility. From the year 2000 until today, food price levels and volatility have more than doubled (see Figures 3 and 4). In this essay, I examine the consequences of this surge in food prices and volatility on household welfare in developing countries. Previous research on this topic has concentrated on the effect of high food prices (Von Braun and Tadesse, 2012) and has confined its analysis to specific regional and time contexts. This essay contributes to the literature in two ways. First, by decomposing the effect of food price variation in permanent shocks (trend), volatility, short- to medium-term changes and sustained episodes of hikes and drops in prices. Second, by extending the regional and time perspective of analysis through the application of a pseudo panel approach, an idea first introduced by Deaton (1985).

The empirical analysis combines macroeconomic information on global food prices from the International Monetary Fund (IMF) and the World Bank (WB) with household-level microeconomic data from the Demograhic and Health Surveys (DHS). This results in a pseudo panel containing information on 38 countries during the period from 1991 to 2011. In the pseudo panel approach, cohorts defined on the basis of a time-invariant characteristic are followed over time. The resulting pseudo panel of cohort means may, therefore, suffer from measurement error. To address this issue, I apply an errors-in-variables (EIV) model based on Deaton (1985) and Verbeek and Nijman (1992). The choice of the appropriate estimator and cohort definition is guided by Monte Carlo Simulations (MCS) which suggest that the Verbeek and Nijman (1992) estimator is the best choice for the prevailing data situation.

Based on this methodology, I find that the variation in global food prices has a negative impact on household welfare in developing countries. The impact is transmitted through the long-term price trend, short-term changes in prices as well as volatility. I find mixed results on the impact of short-term fluctuations around a trend and episodes of sustained drops in food prices. To illustrate the magnitude of the above effects, I set the parameter estimates in relation to the effect size of education on child health and estimate the impact of the above food price indicators on the rate of child malnutrition.

2 Literature review

Theoretical expectations of the effect of global food prices on domestic households are, a priori, indeterminate and depend on macroeconomic factors as well as household characteristics.[1] To start, global commodity prices do not affect domestic producers and consumers directly and there

[1] The price formation of commodity prices has been subject to academic scholarship for a long time. Historically, a large body of literature has evolved about the exploitation of a limited resource, the implied price paths of the resource (Hotelling, 1931) and sustainable pathways of growth in the face of limited resources. Krautkraemer (1998) undertakes an encompassing survey of this literature. Academic discourse has also evolved around the role of competitive storage in price formation (Deaton and Laroque, 1996). More recently, there is a vivid debate on the existence of super cycles (Erten and Ocampo, 2013) and the role of financial speculation (e.g. CBC (2008); Robles et al. (2009); Sanders and Irwin (2010)) in price formation. Headey and Fan (2008) assess the state of the literature on the recent drivers of food prices. Among the discussed explanations, they find that commodity-wide drivers, in particular oil prices, the depreciation of the USD and biofuels have contributed to the rise in food prices. The authors are rather skeptical of the following potential explanations for the recent hike in food prices which are also discussed in the literature: declining stocks, low interest rates and financial speculation. Apart from these general drivers of commodity prices, the authors find that also commodity-specific factors have played an important role (in particular export restrictions for rice and to a lesser extent weather shocks for wheat).

is no consensus as to which extent global prices pass through to domestic markets. Analyzing FAO data from 1961-85, Mundlak and Larson (1992) have found that "most of the variation in world prices are transmitted and that they constitute the dominant component in the variation of domestic prices". Hazell et al. (1990) argue that price variability has been fully transmitted to developing countries but real exchange rate movements, domestic marketing arrangements and government interventions have played a buffering role such that variability has not been fully transmitted to producers' selling prices. Morisset (1998) suggests that while upward movements in prices are transmitted to domestic prices, downward movements are not or only imperfectly transmitted to domestic consumer prices. Baffes and Gardner (2003) are more skeptical of price transmission and find that market integration is high only for some countries and for the remaining countries only few country-commodity pairs show pass-through of world price changes. Dawe (2008) finds partial transmission of world prices to the seven Asian countries in his sample. To sum up, even though the extent of transmission is subject to academic debate, there is no doubt that world prices are, at least partly, transmitted to domestic markets whereby the magnitude of pass-through may vary by country and commodity.

Given partial pass-through, global food prices may affect domestic households' actions and welfare. The micro-economic literature on the consequences of food price changes on household welfare currently evolves in two directions: A literature which attempts to simulate the first-order effects of increases in food prices and an empirical literature which examines the observed consequences of the recent hike in food prices in specific regional and time contexts. In the following, I will discuss the findings of these literatures in turn.

In his seminal paper, Deaton (1989) models how food prices affect households depending on their position as a net producer or net consumer of agricultural goods. In his model, household utility depends on wages, rental income, profits from farming or other business and prices. Deaton (1989), then, derives an intuitive measure for the welfare change due to the price change, which he defines as the amount of monetary compensation that a household would require to maintain its previous level of welfare:

$$\frac{dB}{x} = \left(\omega_i - \frac{p_i y_i}{x}\right) dln(p_i) \tag{1}$$

$\frac{dB}{x}$ is the amount of compensation expressed as a fraction of household expenditure x, ω_i signifies the expenditure share for good i, $\frac{p_i y_i}{x}$ is the value of production of good i as a share of household's total expenditure. Hence, $\omega_i - \frac{p_i y_i}{x}$ is the net consumption ratio which determines whether households benefit or are hurt from price increases in the short run. This approach abstracts from medium- to long-term adjustments in consumption and production decisions by the household in response to the changed price.

Framing the issue in terms of net producers versus net consumers as outlined in Deaton's (1989) model has become the predominant approach to the analysis of microeconomic consequences of food price shocks. Many authors have used this framework to simulate first order effects of an increase in food prices (e.g. Deaton (1989); Barrett and Dorosh (1996); Zezza et al. (2008); Ivanic and Martin (2008); Wodon et al. (2008); Aksoy and Isik-Dikmelik (2008)). Others have taken a related approach and simulated the impacts of food price shocks based on previously estimated demand systems (e.g. Anríquez et al. (2013); Iannotti and Robles (2011)) or Computable General Equilibrium (CGE) models (e.g. Arndt et al. (2008)).

Overall, the literature suggests that adverse effects of increased food prices outweigh positive effects for the poor in most developing countries, at least in the short run (Zezza et al. (2008); Ivanic and Martin (2008); Iannotti and Robles (2011)). The poor spend a high share of their total expenditure on food (Deaton, 1989; Cranfield et al., 2007) and are predominantly net consumers, not only in urban but also often in rural areas (Arndt et al., 2008; Ivanic and Martin, 2008; Aksoy and Isik-Dikmelik, 2008), which makes them vulnerable to food price shocks. On the other side of the equation, there are also winners to increased prices. Zezza et al. (2008) find that those with access to land and productive inputs to agriculture can gain – even if they are part of the poorer households.[2]

There are further exceptions to the stylized fact that price increases are hurting lower income households: Based on his model and data on household food expenditures and production in Thailand, Deaton (1989) predicts that higher prices for rice are overall beneficial to rural households at all wealth strata in Thailand. Strikingly, the benefits of higher rice prices do not tilt the income distribution towards the rich; it is the middle income farmers who benefit most, as net sales make up for an important portion of their income while relatively few rich are engaging in rice farming (Deaton, 1989). Aksoy and Isik-Dikmelik (2008)[3] find that even though most of the poor are net buyers of food, almost half of them are only marginal net buyers and would hence not be hit very hard by increases in food prices. Because most of the rich do not engage in agriculture, an increase in food prices shifts income from higher incomes to lower incomes. This finding changes when the authors confine their analysis to the poor only: Among the poor, net sellers are richer than net buyers in five countries and net buyers only in one country subject to their analysis.

Furthermore, the impact of food price hikes can be heterogeneous according to the specific commodity and country. For instance, even though Ivanic and Martin (2008) predict that for most countries of their sample[4] the welfare losses of the relatively poor outweigh the gains resulting in increased overall poverty (both in terms of poverty headcount and poverty gap), beef is an exception to this pattern. Increases in the price of beef are predicted to reduce poverty in Cambodia and Peru.

Ravallion (1990) develops a framework which also takes into account adjustments in agricultural wages. He derives conditions under which households in rural poor areas, which are net suppliers of labor and net consumers of agricultural goods, can benefit from increases in food prices: If the price elasticity of the wage rate exceeds the net food expenditure to income ratio, the rural poor can gain from increases in food prices. Ravallion (1990) applies this theoretical framework to the case of Bangladesh and finds that, in the short run, the rural poor are negatively affected by price increases (while the rural rich gain) but the welfare effect is rather neutral in the long run after adjustments in wage rates. The welfare effect varies among the poor with

[2]The analysis is based on information from the RIGA database on eleven countries (Africa: Ghana, Malawi; South and East Asia: Bangladesh, Nepal, Pakistan, Vietnam; Eastern Europe and Central Asia: Albania, Tajikistan; Latin America: Guatemala, Nicaragua, Panama)

[3]The authors examine the characteristics of net food buyers and sellers in the eight countries Bangladesh, Cambodia, Vietnam, Bolivia, Nicaragua, Peru, Ethiopia, Madagascar and Zambia.

[4]Bolivia, Cambodia, Madagascar, Malawi, Nicaragua, Pakistan, Peru, Vietnam, Zambia

likely positive effects for the very poor; however, in general, positive effects can only be expected to outweigh the negative effects after three to four years.

Dessus et al. (2008) have attempted to quantify the welfare effects of the recent increases in food prices on urban households and find that the compensation costs of the 2005-7 increase in food prices represent less than 0.2 per cent of GDP for most countries. However, for some countries the cost can exceed 3 per cent. The welfare losses are mainly due to the negative real income effect on households which were already poor before the price hike. "New" households falling into poverty only represent a small share of the cost.[5,6]

The literature discussed so far relies on Deaton's model, estimated demand systems and to a lesser extent CGE models. This literature has made an important contribution in predicting first order effects, developing conditions under which the rural poor can gain (loose) and in identifying vulnerable households which can be expected to experience negative consequences of increases in food prices – a question with great relevance and importance, especially, for the design of policies which aim to mitigate the consequences of the recent hikes in food prices. However, this literature still leaves room for future research. First, the empirical analyzes usually exploit either descriptive information on expenditure shares and production or use between individual heterogeneity to determine the response of households to price increases. It is not clear how households react when they are hit by more extreme shocks (crisis times) and whether the association of consumption and food prices is the same between households and within households over time. Second, all of the simulation approaches rest on complex methodologies which themselves rely on a number of assumptions (e.g. in the construction of a poverty line, a minimum caloric intake). Results may be sensitive to the chosen assumptions, even if reasonable and necessary for simplification, and to the distribution of individuals around the constructed thresholds. Third, the focus on simulations has led to relatively little attention to the "observed" consequences of changes in food prices on household welfare in the academic literature[7] and for this reason needs to be complemented with empirical approaches.

There have been attempts to estimate the empirical effects of high food prices in particular regional and time contexts. These empirical studies mainly focus on child health as a dependent variable and their results are mixed: Some studies find a negative effect of high food prices on child health and some cannot identify such an effect.

Block et al. (2004) estimate the impact of Indonesia's drought and financial crisis in 1997/8

[5]Dessus et al. (2008) estimate the monetary cost (based on the change in an Atkinson (1987)-style "poverty deficit") to compensate for the costs of the 2005-7 increase in food prices based on the Global Income Distribution Dynamics (GIDD) dataset which comprises 72 household surveys on low and middle income countries.

[6]Anríquez et al. (2013) come to a similar conclusion in finding that many poor were already undernourished before the hike in food prices. Anríquez et al. (2013) simulate households' food demand responses to a food price shock based on estimated demand systems in 8 countries using the survey database RIGA. In doing so, the authors use nutritional attainment as a measure of welfare. In this approach, persons are considered undernourished when they fall below a minimum energy requirement. The authors find an increase in undernourishment as a consequence of price increases; the effect is less pronounced for the poor because many of them are already below the minimum energy requirement. The impact is mainly driven by the three factors: dietary patterns (reliance on the main staple foods), staple farm income and the concentration of households around the dietary threshold. The authors further decompose the effect in mean and distributional effects and find that the distributional effect increases undernourishment in most of the analyzed countries.

[7]In the policy world, there is a large amount of case studies and qualitative research available on the consequences of food prices and qualitative and quantitative assessments of the effectiveness of interventions carried out by organizations working on Food Security such as the World Food Program (source: http://www.wfp.org/content/revolution-food-aid-food-assistance-innovations-overcoming-hunger, site accessed: Nov 3, 2013).

on child health measured by weight-for-age (WAZ).[8] Interestingly, the WAZ of children remained constant during the crisis despite the surge in food prices. The authors suggest that mothers buffered the nutritional impact on their children resulting in observed increased maternal wasting. In addition, the authors find that micronutrient status declined for both women and children and observe higher incidence of maternal and child anemia.

Waters et al. (2004) analyze child health status (WAZ) in Indonesia from 1992-1999 based on pooled cross sectional data. They find that the household characteristics of family income, mother's education and source of water are predictors of higher WAZ. In line with the analysis of Block et al. (2004), the authors could not identify an effect of the 1997-99 crisis (which went hand in hand with increases in food prices) on child health. However, during 1997 to 1998 adult malnutrition (measured by Body Mass Index, BMI) did slightly deteriorate which the authors interpret as a possible consequence of parents trying to shield their children from health consequences "at their own expense".[9]

Sulaiman et al. (2009) compare child health status in Bangladesh in 2006 and 2008 – years which have seen stark increases in rice (increase of over 94 per cent) and wheat prices (increase of over 106 per cent). The authors run paired t-tests to investigate the change in childrens' weight-for-height z-score (WHZ) and mothers' BMI. For the rural sample for which panel data is available, the authors also apply a multivariate regression model with household fixed effects. For the urban sample, the analysis relies on cross sectional data. Sulaiman et al. (2009) find a significant deterioration[10] in child health (WHZ) for both rural and urban areas of the magnitude of approximately -0.1 standard deviations (SD). In the same period, mothers' BMI had improved significantly in rural areas and had not changed significantly in urban areas. The effect of food prices is estimated by a year-dummy for the year 2008. Hence, all variation in WHZ which is collinear with this dummy is attributed to the price effect. In their quantitative and qualitative analyzes, the authors find evidence that the composition of children's (and households') diets changed and suggest this could be the primary mechanism through which the worsening of child health status operated.

In his analysis of the patterns of food consumption and nutrition in Bangladesh, Ahmed (1993) analyzes the consequences of a 20 per cent fall in rice prices from the lean season 1991 to 1992. Based on data collected by the International Food Policy Research Institute (IFPRI), the author finds that households are highly responsive to this change and decreased their wheat consumption to increase their rice, meat, milk and egg consumption as well as overall calorie intake. At the same time, adult nutritional status improved and a decrease in undernourished children was observed.

De Brauw (2011) analyzes the role of remittances in mitigating the adverse effect of food price shocks in El Salvador based on survey data from 2008. During 2008, El Salvador experienced a 15 per cent increase in food prices which was associated with a deterioration in the child height-for-age z-score (HAZ) by 0.2 SD on average. De Brauw (2011) found that, during the period of the price hike, households that send out migrants and/or receive remittances from abroad tended to have higher child HAZ.

[8]In their analysis, the authors create birth-cohorts based on fourteen repeated cross sections and decompose trends into time, age and cohort effects.

[9]This effect has been described as "sacrifice effects" in other contexts, see Li and Wu (2011).

[10]For urban households, the result is only significant at the 10 per cent level of significance.

In the context of Malawi, Wood et al. (2012) analyze whether agricultural households who focus on cash crop production are more vulnerable to price shocks than those who engage in traditional maize farming. In 2001, due to severe drought, Malawi experienced a sharp increase in maize prices. Based on the 2004-5 nationally representative Malawi Integrated Household Survey, the authors investigate whether the in utero exposure to this food price shock has led to deteriorated health status (HAZ) in children later on. Using an instrumental variables approach, Wood et al. (2012) find that while during stable times there is no effect of cash crop production on child health status, there is a negative association between child health and households engaging in cash crop farming during the 2001 increase in maize prices. This result indicates that children of cash crop producers are more vulnerable to food price shocks in staple foods such as maize.

Finally, if child health is understood as the outcome of a child health production function, several inputs have to be considered in addition to the food price shocks. A related literature has identified determinants of malnutrition, mainly focusing on household-level determinants (e.g. Hadley et al. (2012); Nakabo-Ssewanyana (2003); Saha et al. (2009)).[11,12] In their meta-analysis of the academic literature on child nutritional status and mortality, Charmarbagwala et al. (2004) identify the socio-economic factors which have been found to determine child health.[13] Those factors are of great relevance for this essay and for this reason, if they dispose of sufficient within-cohort variation and are feasible to implement, are included as control variables.[14] Charmarbagwala et al. (2004) find that the overall evidence in the literature indicates a significant negative effect of mother's education, household wealth, access to water and sanitation on child mortality and a positive effect on nutritional status. The authors also find a negative effect of access to electricity on child mortality and a positive effect of an urban dummy, father's education and a female-headed household dummy on nutritional status.

A related literature has found that early health status has persistent effects in determining later life outcomes such as health status and educational outcomes (e.g. Alderman et al. (2001, 2006); Porter (2010)). This literature links to Heckman and Cunha's (2007) theoretical work on the technology of skill formation which points to (dynamic) complementarities between different dimensions of child development and emphasizes the importance of early child development for later outcomes. Porter (2010) shows that in the context of Ethiopia, food aid had a positive and lasting impact on later health status (ten years later).[15] Successful examples like the one analyzed by Porter (2010) demonstrate that the hands of policy makers are not tied when food price shocks occur. For the design of policies and programs which succeed in delivering enhanced food security and health, it is essential to better understand how households are affected by food price shocks.

The empirical micro-economic literature has so far confined its analysis to specific regional and time contexts. Furthermore, due to the mainly cross-sectional nature of analysis, the literature was unable to decompose the price variation and to attribute the effects to specific components of

[11] Nakabo-Ssewanyana (2003) find that in Uganda households with older women, larger household size, lower female education and low income are more likely to have malnourished children.

[12] Hadley et al. (2012) found that maternal distress is associated with lower child health and some portion of the food insecurity effect is mediated through this variable.

[13] The authors also evaluate the effect of biological and demographic factors and health services on child health from which I abstract in this study.

[14] The household-level controls include an urban dummy, years of education of the mother and male partner, employment in agriculture or self-employment in agriculture, improved water facilities, improved sanitation facilities and a wealth index. No control for female-headed households is included in the analysis.

[15] The author also finds that stunting in early years doubles the probability of stunting in early adolescence.

the variation in food prices – i.e. are the results driven by the trend, fluctuation around the trend or volatility? This essay intends to contribute to the literature by providing insights into these questions and by broadening the regional and time scope of analysis. Based on information on approximately 500,000 children covering 38 countries in the period from 1991 to 2011, I provide a world wide picture of how the variation in food prices has affected household welfare.

3 Research question and model

In their review, Von Braun and Tadesse (2012) find "that the current body of literature concentrates on high food prices" and stress the importance to differentiate between types of price changes which reflect long-term (trend) and short- to medium-term price changes (volatility, spikes). The aim of the following empirical analysis is to bridge this gap in the literature by decomposing the variation in food prices in volatility (coefficient of variation), price spikes (price change in per cent), trend, short-term fluctuation, and sustained periods of price increases and decreases, which I will refer to as price hikes and price drops.[16] The analysis, then, attempts to identify the impact of these types of variation in food prices on household welfare. I choose to proxy household welfare, with child health[17] and operationalize child health as the weight-for-age z-score (WAZ) which is sensitive to short-term changes in child health[18]. The change in WAZ is a good proxy for household welfare effects for two reasons:

First, "when food price or income shocks occur, poor households adopt a series of food and nonfood coping strategies to protect their basic needs; in this context, maintaining their energy consumption level is one of their most fundamental concerns" (Ruel et al., 2010). Food coping strategies may include reducing calorie intake, switching to cheaper and lower quality foods and changing the intra-household allocation of resources. These strategies may have direct adverse consequences for household members, in particular children (Ruel et al., 2010). Other non-food coping strategies (e.g. wife seeking outside employment, child labor, reduced spending on education and other non-food expenses) may only show negative consequences in the longer-term. When investment in child human capital (health, education) is constrained, this is likely to perpetuate inter-generational poverty transmission (Ruel et al., 2010).

The existence of food and nonfood coping strategies and different time-horizons in the realization of impacts on household welfare has implications for the interpretation of the econometric analysis in this essay: If effects on the nutritional and health status of children can be observed, this signifies that the shock must translate into the households with considerable strength such that the households are not able to absorb those shocks through neither insurances and capital markets nor the mentioned coping strategies which do not rely on reducing or changing food consumption. If, nevertheless, an effect is identified, we can assume that the price changes have had strong effects on the household welfare – likely beyond child health. Therefore, child health can be considered a conservative indicator for the consequences of food price shocks.

Second, child health is a meaningful development indicator as it also predicts some longer-term consequences of food price shocks: Early child health is an important determinant of later health status (Alderman et al., 2006), education (Alderman et al., 2001) and wealth (Currie, 2009); for this reason, child anthropometrics also capture long-term consequences of price shocks.

In the below model, child health[19], as a proxy for household welfare, is regressed on the food price indicators (FPI, Figures 3 and 4) and a set of control variables which have been identified by the literature as major determinants of child health status. The control variables include access to improved water supply and sanitation infrastructure, years of education of the mother

[16] For the definition of the concepts, see data and definitions.

[17] In this analysis, the term "child health" refers to the health status of children until the age of five.

[18] For more technical information on the calculation of the indicator, see the section data and definitions.

[19] The anthropometric measure WAZ is calculated for children until the age of five. This reflects the data availability of the DHS surveys.

and father, employment status (agricultural employment, agricultural self-employment, other), a wealth index, logarithmic GDP per capita and a time trend t_t. The time trend is included to control for an overall trend in macroeconomic variables which may otherwise be captured by the coefficients on the food price indicators (in particular the food price index and the trend). The model is formalized in equation 2 whereby the index *int* refers to a given individual i, in country n at time t, α_i is individual-specific time-invariant heterogeneity and ϵ is an error term.

$$\begin{aligned}\mathrm{WAZ}_{int} = \beta_0 + \beta_1 \mathrm{FPI}_t &+ \beta_2 \text{ improved water supply}_{int} + \beta_3 \text{ improved sanitation}_{int} \\ &+ \beta_4 \text{ maternal education}_{int} + \beta_5 \text{ paternal education}_{int} \\ &+ \beta_6 \text{ agr. employment}_{int} + \beta_7 \text{ agr. self-employment}_{int} \\ &+ \beta_8 \text{ urban}_{int} + \beta_9 \text{ wealth}_{int} + \beta_{10} \text{ GDP}_{nt} + \beta_{11} t_t + \alpha_i + \epsilon \qquad (2)\end{aligned}$$

In the following section, I describe the identification strategy of this essay which is based on Deaton's (1985) error-in-variables model for repeated cross sections. The approach allows combining macroeconomic data on global food prices with microeconomic data at the household level while controlling for individual effects α_i.

4 Identification strategy

To lay out the identification problem, it is informative to start off with a simple linear model of pooled cross-sections. In doing so, I rely on Verbeek's (2008) discussion. Equation 3 states the model whereby y_{it} denotes the health status of child i at time t, x'_{it} is a K-dimensional vector of explanatory variables, α_i is an individual fixed effect and β is the coefficient vector of interest. If the individual effects α_i were uncorrelated with the explanatory variables, we could estimate the model consistently by pooling the repeated cross sections and running an OLS estimation on the pooled sample. Even though this assumption has the potential to greatly simplify our lives (and is frequently made in empirical approaches), it does not seem realistic in the context of our estimation problem: Some of the explanatory variables are household and individual characteristics and it is therefore likely that they are correlated with the individual effects. Let's assume $E\{x_{it}u_{it}\} = 0$ and $E\{x_{it}\alpha_i\} \neq 0$.

$$y_{it} = x'_{it}\beta + \alpha_i + u_{it}, \quad t = 1,...,R \quad and \quad i = 1,...,N \tag{3}$$

When some of the explanatory variables are correlated with the individual effects, then at least some of the K moment conditions $E\{(y_{it} - x'_{it}\beta)x_{it}\} = 0$ are invalid, resulting in biased estimates for all coefficients β. In the context of a panel structure, this issue can be remedied by the use of a within-individual estimator (fixed-effects estimator) controlling for all individual-specific time-invariant heterogeneity. In the absence of genuine panel data, this option is not available due to a lack of information on the individuals' history. In his seminal paper, Deaton (1985) suggested that, in situations where repeated cross sections are available, one can resort to a cohort-based pseudo panel approach in which the idea is the following:

Based on the model in equation 3, C cohorts which consist of individuals with a common time-invariant characteristic can be defined. The time-invariant characteristic should assign each individual to a unique cohort. This assignment needs to remain the same across time such that if an individual from an earlier cross section would be drawn into one of the samples of a later cross section, it would end up in exactly the same cohort. In this essay, cohorts are defined based on birthyear brackets and the country of residence.[20] By transforming the pooled cross section to a model of cohort means using this cohort definition, we obtain the pseudo panel (or synthetic panel) model in equation 4.

$$\bar{y}_{ct} = \bar{x}_{ct}\beta + \bar{\alpha}_{ct} + \bar{u}_{ct}, \quad c = 1,...,C \quad and \quad t=1,...,R \tag{4}$$

Choosing a meaningful cohort definition is crucial to this approach because the parameters can only be identified if the cohort definition generates sufficient variation over time (Verbeek, 2008). The pseudo panel now contains $T = C \times R$ observations with c referring to the individual cohorts and t to the time period. As in its cross-sectional counterpart, the explanatory variables $\bar{x}_{ct}$ from the synthetic panel are likely to be correlated to the individual cohort effects $\bar{\alpha}_{ct}$. Letting $\bar{\alpha}_{ct}$ be subsumed by the error term will lead to biased estimates as not all K moment conditions $E\{(\bar{y}_{ct} - \bar{x}'_{ct}\beta)\bar{x}_{ct}\} = 0$ can be expected to hold.

[20] I abstract from migration between countries. This simplification is realistic for the largest part of the households and is for this reason unlikely to influence the results.

If we replace $\bar{\alpha}_{ct}$ with $\bar{\alpha}_c$ (i.e. $\bar{\alpha}_{ct}$ is replaced by cohort dummy variables), one can then estimate the model in 4 by OLS or weighted least squares if cohort sizes vary greatly; this estimator has been referred to as the efficient Wald estimator (Angrist, 1991; Devereux, 2007b). In small samples, this estimator is biased due to $\text{cov}(\bar{\alpha}_{ct} - \alpha_c, \bar{x}_{ct}) \neq 0$ (Devereux, 2007b, p. 840).

Until today, there is no consensus in the academic literature as to what cohort size is deemed sufficiently large. While Verbeek and Nijman (1992) consider that "the effects of ignoring the fact that only a synthetic panel is available will be small if the cohort sizes are sufficiently large (100, 200 individuals)", Devereux (2007b) shows that in practice considerable biases can emerge when pseudo panel models are estimated based on cohorts which consist of a size of 100-200 individuals without correcting for sampling errors. Devereux (2007b, p. 839) finds that for his particular application, the estimation of the income elasticity of female labor supply, "thousands of observations per group are required before small-sample issues can be ignored in estimation[...]". Even with cohort sizes of 10,000 observations per cohort, biases of the order of 10 % still persist (Devereux, 2007b).

In applied research, we often encounter heterogeneous cohort sizes of which some are well below 100 individuals per group. To remedy bias due to small cohort size, this essay resorts to Deaton's (1985) approach which corrects for measurement error. Again, the choice of whether or not an EIV estimator is necessary essentially boils down to one's decision on a set of asymptotic assumptions.

Deaton (1985) assumes fixed cohort size n_c while the number of cohorts C tends to infinity ($C \to \infty$). These two assumptions seem realistic in our context where birthyear-country-cohorts are formed and cohort size can be small, sometimes with $n_c < 100$. When more rounds of household surveys become available, this increases the number of cohorts in the dataset but does not affect cohort size. Other authors (e.g. Moffitt (1993)) have assumed that the number of individuals per cohort tends to infinity ($n_c \to \infty$) while C is constant. If the second set of assumptions were applied, one could conveniently abstract from the measurement error problem.

In this essay, I assume that measurement error is substantial and understand the estimation problem as an errors-in-variables problem. If equation 5 is the true cohort model, then the cohort sample means $\bar{y}_{ct}$ and $\bar{x}_{ct}$ in equation 4 are error-ridden estimates of this true model. The individuals which constitute a cohort in the microdata can be considered random draws from the true population[21]. The expected value of the cohort means is the true population mean and the measurement error variance declines with increasing cohort size according to the law of large numbers.

$$y^*_{ct} = x^*_{ct}\beta + \alpha^*_{ct} + u_{ct}, \quad c = 1,...,C \quad and \quad t=1,...,R \tag{5}$$

In following Deaton's (1985) notation, equation 5 can be simplified to equation 6 with a single index t, running from 1 to T. Now, x^*_{ct} also contains the cohort dummies which are not subject to measurement error and are treated as being measured with an error of zero mean and variance. This can also extend to other variables such as country characteristics which do not

[21]Obviously, this assumption only holds if the underlying sampling was representative of the true population which we assume is the case in the Demographic and Health Surveys which are subject to this analysis.

have the measurement error structure of equation 7. To warrant Deaton's (1985) assumption of the error u_t to be normal, homoskedastic and independent over t, the observations need to be weighted by the inverse of the square root of cohort size. The weighting[22] can be obtained by premultiplying all variables by a diagonal weighting matrix $V^{-1/2}$ which is defined such that $P = P' = V^{-1/2}V^{-1/2} = V$.

$$y_t^* = x_t^*\beta + u_t, \text{ t=1,..., } \underbrace{CR}_{=T} \tag{6}$$

[22]For more details, see Greene (2007) or other standard econometric texts.

Deaton (1985) assumes the following measurement structure which corresponds to the properties of classical measurement error:

$$\begin{pmatrix} \bar{y_t} \\ \bar{x_t} \end{pmatrix} = N \begin{pmatrix} y_t^*; & \sigma_{00} & \sigma' \\ x_t^*; & \sigma & \Sigma \end{pmatrix} \tag{7}$$

Following Verbeek's (2008) notation, the above measurement error structure can be re-written as

$$\begin{pmatrix} \bar{y_t} - y_t^* \\ \bar{x_t} - x_t^* \end{pmatrix} = N \begin{pmatrix} 0; & \sigma_{00} & \sigma' \\ 0; & \sigma & \Sigma \end{pmatrix} \tag{8}$$

whereby the true populations values y_t^* and x_t^* can be interpreted as unknown but constant terms. From this notation, it can be seen that the measurement error variances of $\bar{y_t} - y_t^*$ and $\bar{x_t} - x_t^*$ reduce to the variance of the respective means:

$$\sigma_{00} = \mathrm{var}(\bar{y_t} - y_t^*) = \mathrm{var}(\bar{y_t}) + \underbrace{\mathrm{var}(y_t^*)}_{=0} - \underbrace{2\ \mathrm{cov}(\bar{y_t}, y_t^*)}_{=0} = \mathrm{var}(\bar{y_t}) \tag{9}$$

In analogy to the above, $\Sigma = \mathrm{cov}(\bar{x_t})$. Consequently, the covariance vector σ can be derived as follows[23]:

$$\begin{aligned} &\mathrm{cov}(\bar{y_t} - y_t^*, \bar{x_t} - x_t^*) = \mathrm{cov}(\bar{y_t}, \bar{x_t}) = \mathrm{cov}(\beta\bar{x_t} + u_t, \bar{x_t}) \\ &= \beta \times 1 \times \mathrm{var}(\bar{x_t}) + \underbrace{1 \times 0 \times \mathrm{var}(u_t)}_{=0} + (\beta \times 0 + 1 \times 1)\underbrace{\mathrm{cov}(\bar{x_t}, u_t)}_{=0} \\ &= \beta var(\bar{x_t}) \end{aligned} \tag{10}$$

Since we assume the measurement error to be classical following a normal distribution with zero mean, the moments are well understood. Following Fuller (1981), let us assume $W_t = \{W_{0t} = (\bar{y}_t - y_t^*), W_{1t} = (\bar{x}_{1t} - x_{1t}^*), ..., W_{kt} = (\bar{x}_{kt} - x_{kt}^*)\}$ are random variables whose realizations constitute draws from a multivariate normal distribution with mean zero and covariance matrix χ, where σ_{ij} are the elements of χ. To clarify notation, $s_{yy} = s_{11} = \sigma_{00}$, the elements of σ are $s_{yx_k} = s_{1k}$ and the elements of Σ are denoted $s_{x_j x_k} = s_{jk}$ with $j = 2, ..., k+1$ and $k = 2, ..., k+1$.

We know from the properties of moments of the normal distribution (see Fuller (1981)) that the sample mean has the variance $E\{\bar{W}_i\bar{W}_j\} = n_c^{-1}\sigma_{ij}$. This property can be used to estimate the respective measurement error variances in pooling the cross-sectional datasets. After the cohort means have been removed from the data, σ_{00}, Σ and σ can be estimated by their sample counterparts s_{00}, S_{jk} and s_j, as described in the below equations.

$$s_{00} = \mathrm{var}(\bar{y_t} - y_t^*) = \frac{\sigma_y^2}{n_c} \tag{11}$$

[23]Using the following property of expectations in a joint distributions $\mathrm{cov}(ax + by, cx + dy) = ac\mathrm{var}(x) + bd\mathrm{var}(y) + (ad + bc)\mathrm{cov}(x, y)$, we obtain the next equation (see Greene (2007, p. 1004)).

The diagonal elements of Σ can be estimated

$$S_{jj} = \text{var}(\bar{x}_{jt} - x_j^*) = \frac{\sigma_{xj}^2}{n_c} \tag{12}$$

while the off-diagonal elements are estimated by

$$S_{jk} = \text{cov}(\bar{x}_{jt} - x_j^*\text{t}, \bar{x}_{kt} - x_k^*) = \frac{\sigma_{x_j x_k}}{n_c} \tag{13}$$

and the elements of σ by

$$s_{yx_j} = \text{cov}(\bar{y}_t - y_t^*, \bar{x}_t - x_t^*) = \frac{\sigma_{yx}}{n_c} \tag{14}$$

Based on Fuller (1975, 1981), Deaton (1985) derives the error-in-variables estimator in equation 15. This estimator yields identical results to the jackknife instrumental variables estimator and is closely related to the k-class of instrumental variables estimators (Devereux, 2006).

$$\tilde{\beta} = (M_{xx} - S)^{-1}(m_{xy} - s) = (X'X - TS)^{-1}(X'y - Ts) \tag{15}$$

whereby M_{xx} and m_{xy} are the respective sample moments and cross product matrices, S and s are the sample counterparts of Σ and σ and $\tilde{\Omega} = M_{xx} - S$.

Under the assumption of known error variances, Deaton (1985) derives the variance of the estimator as follows[24]

$$TV(\tilde{\beta}) = \tilde{\Omega}^{-1}\left[T^{-1}X'Xe'e + T^{-2}X'ee'X\right]\tilde{\Omega}^{-1} \tag{16}$$

Under the assumption of estimated error variances, the variance of the estimator becomes slightly more complicated (Deaton, 1985) but can be evaluated straightforwardly in practice.

$$TV(\tilde{\beta}) = \tilde{\Omega}^{-1}\left[\Sigma_{xx}\omega^2 + (\sigma - \Sigma\beta)(\sigma - \Sigma\beta)'\right]\tilde{\Omega}^{-1} + v^{-1}\tilde{\Omega}^{-1}V(s - S\beta)\tilde{\Omega}^{-1} \tag{17}$$

whereby $\Sigma_{xx} = E(M_{xx})$, $\omega^2 = \frac{1}{T}e'e$ and $V(s - S\beta) = \Sigma(\sigma_{00} - 2\sigma'\beta + \beta'\Sigma\beta) + (\sigma - \Sigma\beta)(\sigma - \Sigma\beta)'$ and $v = n_c$.

Verbeek and Nijman (1992) suggest a slightly altered estimator which provides better properties when only few repeated cross sections are available. The estimator is written down in equation 18 whereby $\tau = (P-1)/P$ and P indicates the number of repeated cross sections which are available for the cohorts.[25]

$$\tilde{\beta} = (M_{xx} - \tau S)^{-1}(m_{xy} - \tau s) \tag{18}$$

Which approach fits the data best depends on the specific characteristics of the data. In section **??**, I explore the properties of various estimators using Monte Carlo Simulations (MCS)

[24] This assumption does not greatly change the estimates as will be seen in the empirical part of this essay.

[25] Similarly, Devereux (2007a) suggested an estimator that is approximately unbiased in the case of a small number of cohorts.

based on a data generating process which mimics the data availability. The results from the simulations clearly suggest that the Verbeek-Nijman (1992) estimator outperforms the other estimators (OLS, Cohort Fixed Effects / Efficient Wald and Deaton (1985)) in this context.

5 Data and definitions

The data which underlie this analysis are assembled from three different sources: The Demographic and Health Surveys (DHS)[26], the Commodity Price Indices by the International Monetary Fund[27] and the World Development Indicators from the World Bank[28].

The DHS survey data are ideal as basis for pseudo panel analysis due to their richness in demographic and health information, comprehensive regional coverage, repeated implementation and high degree of standardization between countries and survey rounds. Currently, more than 300 DHS surveys from more than 90 countries are available upon request. The questionnaires of the surveys follow six templates depending on the phase of survey implementation (DHS I to DHS VI). To merge several DHS surveys to a pooled and coherent dataset has obvious challenges. Some information is only available in certain survey phases (and for certain countries) and some variables are coded with country-specific values. Nevertheless, compared to other sources of survey data (e.g. World Bank Living Standards Measurement Study, LSMS), the DHS data is characterized by a high degree of standardization which is crucial for the chosen pseudo panel approach.

All available survey rounds (210 by early 2013) with several repeated cross-sections for a given country and which contain the relevant information for the question of analysis were pooled into one dataset. After the omission of missing values, the pooled child-recode dataset contains information on 497,839 children and their households from 38 countries (see Table 1). This information was then merged with the macroeconomic information on world food prices from the IMF and the World Bank and GDP per capita from the World Bank.

Child health, used as a proxy for household welfare, is measured by an anthropometric indicator, the weight-for-age z-score (WAZ).[29] The WAZ of a child is defined as the distance between the weight-for-age ratio of the given child compared to the median of a reference population[30] (of the same age and sex) divided by the standard deviation (SD) of the reference population. Pathological deficiencies indicated through WAZ are referred to as “underweight”. Usually, a z-score below -2 SD is considered pathological and a z-score below -3 SD severe.[31,32] With annual data, a meaningful indicator of malnutrition needs to show an effect within a given year. In this essay, WAZ is calculated using the Stata command zanthro, an extension to generate standardized anthropometric measures in children and adolescents by Suzanna Vidmar, John Carlin, Kylie Hesketh[33] and Tim Cole[34].

The wealth index is constructed based on Filmer and Pritchett’s (2001) methodology whereby the different types of assets are weighted using principal component analysis. The approach is based on the assumption that most of the variance and covariance in the assets is explained

[26]Source: http://www.measuredhs.com, site visited: July 26, 2013

[27]Source: http://www.imf.org/external/np/res/commod/index.aspx, site visited: July 26, 2013

[28]Source: http://data.worldbank.org/data-catalog/world-development-indicators, site visited: July 26, 2013

[29]The DHS child recode KR contains information on children born in the five years preceding the survey. Hence, children below the age of five (0-59 months of age) are included in the analysis.

[30]In this analysis, the weight-for-age z-score is calculated based on the 1990 British Growth Reference.

[31]See O’Donnell et al. (2008), http://siteresources.worldbank.org/INTPAH/Resources/Publications/Quantitative-Techniques/health_eq_tn02.pdf

[32]The anthropometric indicator WAZ is well suited to the question of analysis since it is responsive to malnutrition in the short term.

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[34]Centre for Paediatric Epidemiology and Biostatistics Institute of Child Health London, UK

by longterm wealth. Filmer and Pritchett (1999),Filmer and Pritchett (2001) and Filmer and Scott (2008) show in their work that wealth indices can function well as a predictor of economic status and are "at least as reliable as conventionally measured consumption expenditures, and sometimes more so" (Filmer and Pritchett, 2001). The assets included in the principal component analysis are radio, television, refrigerator, bicycle, motorbike, car, truck and type of floor material. Due to the fact that the pseudo panel approach only exploits within cohort variation over time (within a country), cross country comparability in the ownership of assets is not an issue.

For access to safe water supply and sanitation, the definitions of the Joint Monitoring Programme (JMP, WHO and UNICEF (2006)) were applied – which are also used for the official United Nations (UN) monitoring of Millennium Development Goal 7c (access to water and sanitation). Due to a lack of information on water quality, the definition uses "improved water and sanitation technologies" as a proxy for access to safe water supply and sanitation. The approach can be justified for practicality reasons but has considerable shortcomings (Schiffler and Ziegelhöfer, 2012) and, in practice, coherent and meaningful coding can be a challenge. The DHS data subject to this essay contains 433 codes for water supply infrastructure and 322 codes for sanitation technologies. Some of the codes can only be assigned to the JMP categories "improved" or "unimproved" under additional assumptions. In coding improved and unimproved water and sanitation technologies, I follow Günther and Fink's (2010) coding rule for the definition of improved and unimproved sources which excludes the categories tanker-trucks and bottled water.

For the information on food prices, I rely on the IMF's food price index. The critical reader may wonder why the analysis does not make use of information from the FAO's database – the usual suspect for information on food prices. The reason for this choice is data availability. For instance, the FAO's consumer price index is only available for the period 2000-2013 and the FAO's producer price index for the period 1999-2010 – relying on one of these indices would therefore have restricted the period of analysis considerably. In addition to its price indices, FAO also offers very rich information on food prices at the country level – disaggregated for various agricultural goods. In this essay, I attempt to estimate how the recent surge in international prices affects the welfare of local households. Using prices at the country-level would change the question of analysis as this approach would abstract from international prices and their pass-through to domestic markets.

For the above reasons, I choose to use the IMF's food price index which reaches back to 1991.[35] The index is based on commodity prices in nominal U.S. dollars and is calculated as the weighted average of the following groups of goods: Cereals (wheat, maize, rice, barley), vegetable oils and protein meals (soybeans, soybean meal, soybean oil, palm oil, fishmeal, sunflower oil, olive oil, groundnuts, rapeseed oil), meat (beef, lamb, swine meat, poultry), seafood (fish, shrimp), sugar, bananas and oranges. The weights of the respective goods are based on 2002-2004 average world export earnings.[36] In the reference year 2005, the value of the index is defined as 100.

Inspired by Von Braun and Tadesse's (2012) work, I decompose the Food Price Index in

[35] An alternative choice could have been the World Bank's index on global food prices from the Global Economic Monitor (GEM) Commodities which extends back even further in time. I re-run the estimation with the World Bank's price series in nominal and real terms as robustness check.

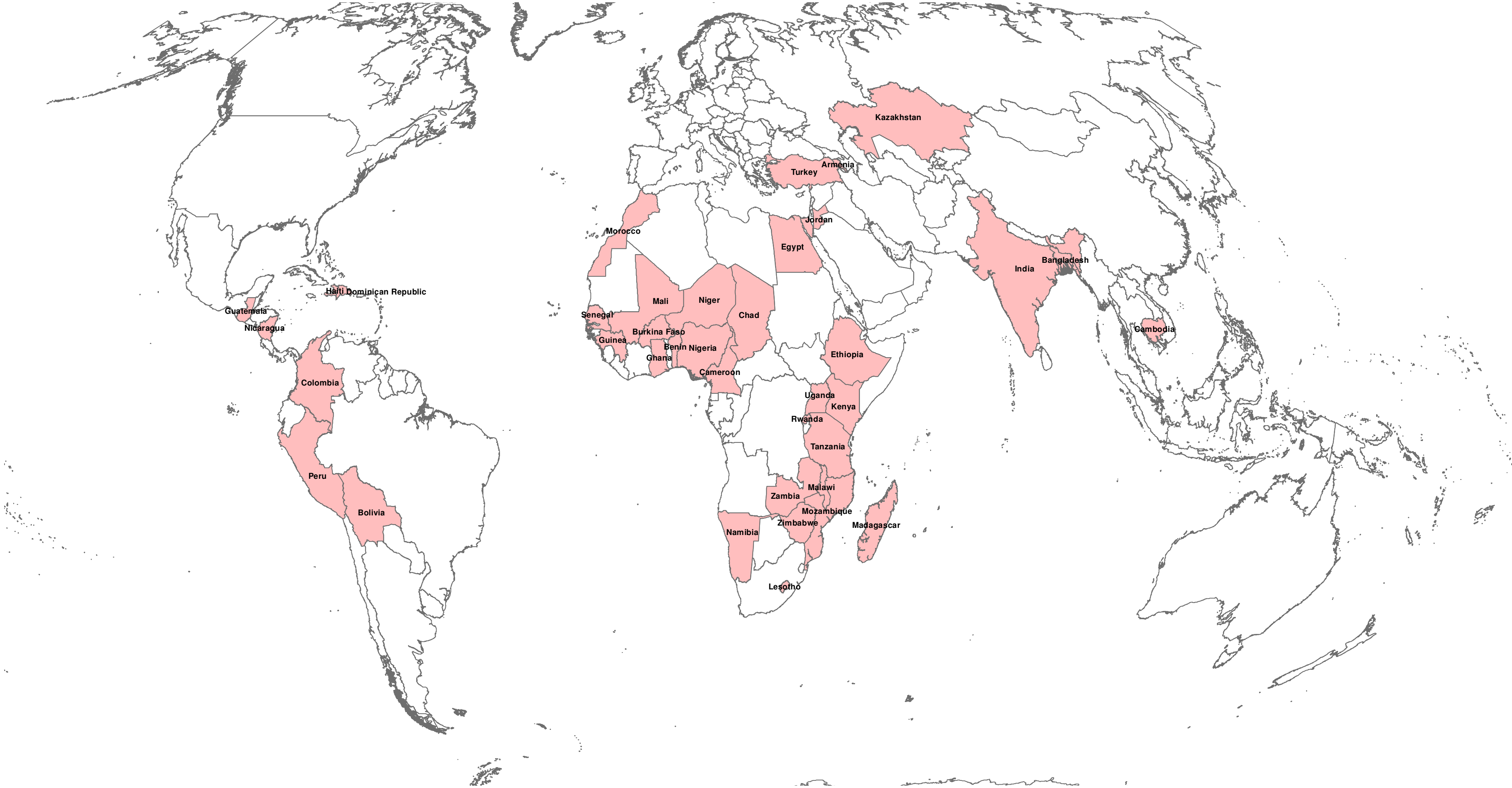
[36] For a detailed description on the included commodity prices and their respective weights in the index see: http://www.imf.org/external/np/res/commod/index.aspx, site visited: July 26, 2013.

volatility (Coefficient of Variation), price change in per cent, trend, short-term fluctuation, and sustained periods of price increases and decreases. Using monthly data of the Food Price Index, I calculate a Coefficient of Variation on an annual basis. Using annual data, I decompose the series in a trend and fluctuation around the trend using a Hodrick-Prescott (HP)-Filter with $\lambda = 6.25$ (Baum, 2004; Ravn and Uhlig, 2002). The percentage change in prices from the previous period to the current period is defined with the previous period as base year. I define episodes of sustained increases (Price Hike) and decreases (Price Drop) as subsequent years of price changes in the same direction. The data on GDP per capita is taken from the World Development Indicators of the World Bank.

Table 1: List of countries and survey years

Country	**Years of DHS data collection**
Armenia	2000, 2005, 2010
Bangladesh	1996, 1997, 1999, 2000, 2004, 2007, 2011
Benin	1996, 2001, 2006
Bolivia	1989, 1993, 1994, 1998, 2003, 2004, 2008
Burkina Faso	1992, 1993, 1998, 1999, 2003, 2010
Cambodia	2000, 2005, 2006, 2010, 2011
Cameroon	1991, 1998, 2004, 2011
Chad	1996, 1997, 2004
Colombia	1995, 2000, 2004, 2005, 2009, 2010
Dominican Republic	1991, 1996, 2002, 2007
Egypt	1995, 1996, 2000, 2003, 2005, 2008
Ethiopia	1992, 1997, 2003
Ghana	1998, 1999, 2003, 2008
Guatemala	1995,1998,1999
Guinea	1999, 2005
Haiti	1994, 1995, 2000, 2005, 2006
India	2005, 2006
Jordan	1997, 2002, 2007
Kazakhstan	1995, 1999
Kenya	1993, 1998, 2003, 2008, 2009
Lesotho	2004, 2005, 2009, 2010
Madagascar	1992, 1997, 2003, 2004
Malawi	1992, 2000, 2004, 2005, 2010
Mali	1995, 1996, 2001, 2006
Morocco	1992, 2003, 2004
Mozambique	1997, 2003, 2004
Namibia	1992, 2000, 2006, 2007
Nicaragua	1997, 1998, 2001
Niger	1992, 1998, 2006
Nigeria	1999, 2003, 2008
Peru	1991, 1992, 1996, 2000, 2005, 2007, 2008
Rwanda	1992, 2000, 2005, 2010, 2011
Senegal	1992, 1993, 2005, 2010, 2011
Tanzania	1991, 1992, 1996, 2004, 2005, 2009, 2010
Turkey	1993, 1998, 2003, 2004
Uganda	1995, 2000, 2001, 2006, 2011
Zambia	1992, 1996, 1997, 2001, 2002, 2007
Zimbabwe	1994, 1999, 2005, 2006, 2010, 2011

Figure 1: Map of countries in sample, elaboration of map with ArcGIS by Sven Kristen.



Definition of cohorts

The definition of cohorts (or pseudo individuals) based on the pooled household data is a crucial step in the analysis. Three issues are of importance: First, the cohort definitions need to be based on time-invariant criteria such that an individual drawn into the sample in two survey rounds would always end up in the same cohort. This restriction rules out all characteristics which change in the course of time. Second, the pseudo panel based on this cohort definition needs to contain sufficient time-variation (within pseudo-individual variation) such that the parameters of interest can be identified. Third, the above discussion (on the asymptotics) and the Monte Carlo Simulation (MCS) in section **??** show that there is a trade-off between creating large cohorts to minimize measurement error and creating many cohorts to maximize efficiency (i.e. obtain small standard errors). With these issues in mind, I will now discuss the choices made in the construction of the pseudo panel in this analysis.

In this essay, a cohort definition based on the country of residence[37] and the birth year of the mother of the concerned child is chosen. This choice reflects the data structure of DHS. For the DHSs, primarily women between 15 to 45 are surveyed; for this reason the information on women is much richer[38] than the information contained on their partner – for instance, not all surveys contain information on the age of the partner. As a result of this choice, the analysis exploits the within-mother-cohort variation to identify the effect of food price shocks on child health. The analysis can then be understood as a panel model with mother-cohort-fixed effects. Table 4 indicates that the synthetic panel disposes of a reasonable amount of within variation – whether it is sufficient to identify the parameters is eventually an empirical question.

To study the mentioned trade-off in the definition of cohorts, I explore the properties of the estimators using Monte Carlo Simulation (MCS). The MCS shows that the Verbeek-Nijman estimator is already approximately unbiased with a cohort size between 30–50 individuals per cohort. If cohort size falls below this minimum size, the bias of the estimator increases considerably. By ensuring that cohort size is above this threshold and maximizing the number of cohorts in the panel, the efficiency of the estimator can be increased. Hence, the Verbeek-Nijman estimator performs best in terms of bias and root mean square error when the number of cohorts is maximal given a relatively small minimum number of observations per cohort. The results from the simulations and their implications are described in more detail in section **??**.

[37] I abstract from migration between countries which seems reasonable given the relatively rare event for the surveyed population.

[38] Reporting of the age of the respondent in the DHS surveys is almost universal; there are only few missing entries because the eligibility of interview is based on this information. If information on the date of birth was missing, the imputation error was limited to 12 months range in the worst case (Croft, 2013).

For the above reason, I chose a cohort definition such that the cohort size (individuals per cohort) is above the mentioned threshold for most cohorts and distributed as evenly as possible between cohorts. Due to the fact that cohort size varies in empirical applications (i.e. cannot be fixed to a certain number as in the MCS), I choose a definition such that the mean and median cohort size stay considerably above the suggested minimum bound to minimize the number of cohorts which fall below the optimal cohort size – sacrificing some efficiency for reduced measurement error. To achieve this, I define the birth year bands unevenly according to the observed density of the pooled data for each country. Each cohort (note: not each cohort in every year) contains a minimum of 0.5 per cent of the total observations of the pooled information on a country which results in a median cohort size of 59 and mean cohort size of 102. More than two-thirds of the cohorts dispose of a cohort size larger than 30 individuals per cohort. Figure 2 illustrates the distribution of individuals per cohort.

Table 2: Descriptive statistics on pooled cross sections, number of observations: 497,839

var	min.	1st qu.	median	mean	s.d.	3rd qu.	max.
WAZ	-5	-2.14	-1.19	-1.2	1.43	-0.28	5
Food Price Index	80.15	88.56	100.9	108.9	26.06	112	178.8
Coefficient of Variation	1.5	3.28	4.42	5.15	3.03	5.85	13.81
percentage change in FPI	-0.16	-0.01	0.06	0.06	0.09	0.11	0.21
HP Filter	-12.38	-4.69	-1.61	0.56	7.3	2.07	19.79
HP Trend	83.15	89.72	101.2	108.3	22.97	115.2	165.01
Price Hike	0	0	0	0.37	0.48	1	1
Price Drop	0	0	0	0.07	0.26	0	1
Improved Water Supply	0	0	1	0.67	0.47	1	1
Improved Sanitation	0	0	0	0.35	0.48	1	1
Wealth Index	-1.98	-1.60	-0.43	0.04	1.82	1.61	4.48
Agricultural self-employment	0	0	0	0.50	0.76	1	2
Agricultural employment	0	0	0	0.18	0.46	0	2
Maternal Education in years	0	0	4	4.61	4.62	8	23
Paternal Education in years	0	0	5	5.79	5	10	26
Log. GDP per capita	4.63	5.66	6.2	6.37	0.92	7.3	8.43
Birthyear	1941	1967	1974	1973	8.44	1980	1996
Advanced WS technology	0	0	0	0.44	0.5	1	1
Basic WS technology	0	0	0	0.40	0.49	1	1
Urban	0	0	0	0.34	0.47	1	1
Year	1991	1999	2003	2002	5.38	2006	2011
Nr. of repeated cross sections	2	3	4	4.14	1.53	5	7

Figure 2: Boxplot of cohort sizes in pseudo panel

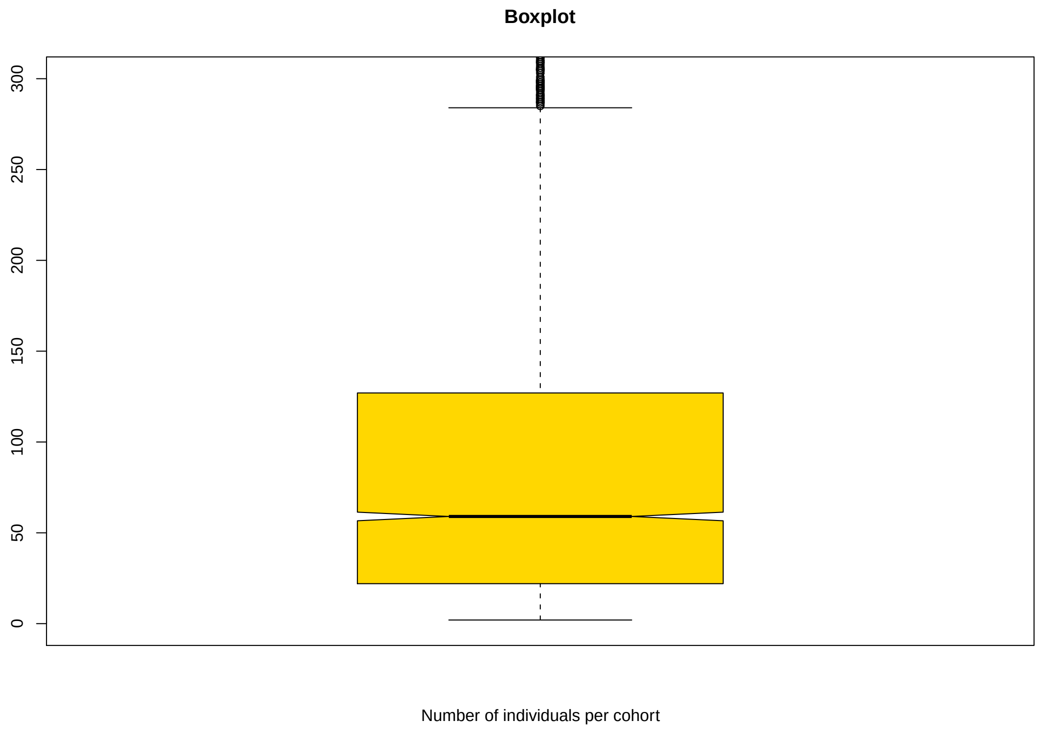


Table 3: Univariate distribution of cohort sizes in pseudo panel

per centile	n_c
5	4
10	8
30	28
50	59
80	148
90	235
95	334

Table 4: Descriptive statistics on pseudo panel, number of pseudo individuals: 1247, number of observations in pseudo panel: 4877

var	category	mean	sd	min	max	obs
WAZ	overall	-1.19	.59	-3.75	1.49	4877
	between		.52			
	within		.29			
Food Price Index	overall	106.86	24.9	80.16	178.78	4877
	between		13.03			
	within		21.94			
Coefficient of Variation	overall	4.77	2.54	1.5	13.81	4877
	between		1.19			
	within		2.3			
percentage Change in FPI	overall	.033	.09	-.16	.21	4771
	between		.05			
	within		.08			
HP Filter	overall	.2	6.69	-12.38	19.79	4877
	between		3.26			
	within		5.94			
HP Trend	overall	106.66	22.67	83.15	165.01	4877
	between		12.86			
	within		19.35			
Price Hike	overall	.36	.48	0	1	4877
	between		.25			
	within		.42			
Price Drop	overall	.13	.34	0	1	4877
	between		.22			
	within		.27			
Improved Water Supply	overall	.65	.28	0	1	4877
	between		.23			
	within		.15			
Improved Sanitation	overall	.3	.29	0	1	4877
	between		.25			
	within		.16			

var	category	mean	sd	min	max	obs
Wealth Index	overall	-.14	1.20	-1.98	4.05	4877
	between		1.15			
	within		.42			
Agricultural self-employment	overall	.60	.52	0	2	4877
	between		.45			
	within		.28			
Agricultural employment	overall	.14	.25	0	1.75	4877
	between		.22			
	within		.16			
Maternal education in years	overall	4.19	2.67	0	17	4877
	between		2.61			
	within		1.05			
Paternal education in years	overall	5.26	2.71	0	17	4877
	between		2.56			
	within		1.16			
GDP per capita	overall	6.34	.92	4.63	8.42	4877
	between		.91			
	within		.13			
Time trend	overall	11.48	5.63	1	21	4877
	between		3.53			
	within		4.64			
Advanced WS technology	overall	.44	.31	0	1	4877
	between		.27			
	within		.15			
Basic WS technology	overall	.38	.29	0	1	4877
	between		.23			
	within		.16			
Urban	overall	.33	.23	0	1	4877
	between		.19			
	within		.14			

Figure 3: Time series of the IMF food price index (in nominal U.S. dollars) and its decomposition

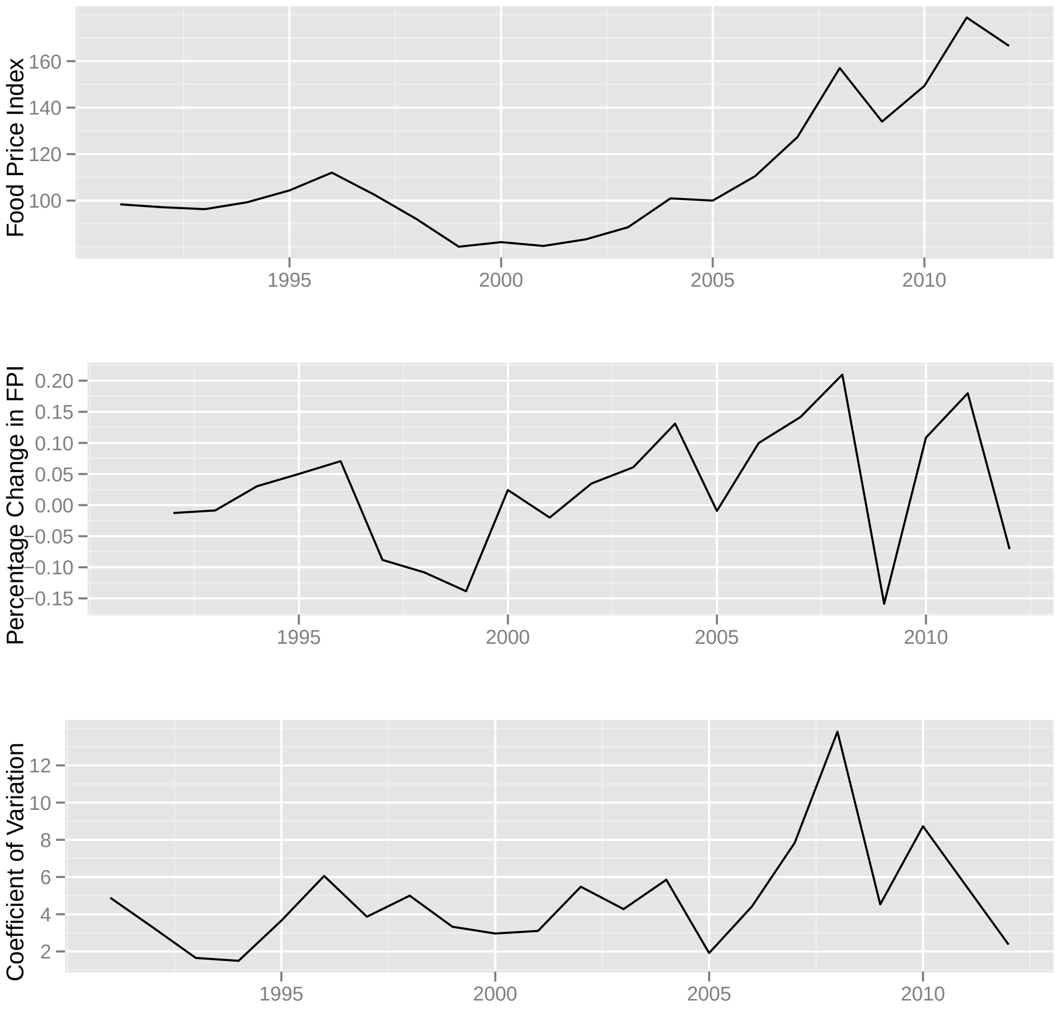


Figure 4: Decomposition of IMF food price index in trend and short-term fluctuation, HP filter ($\lambda = 6.25$)

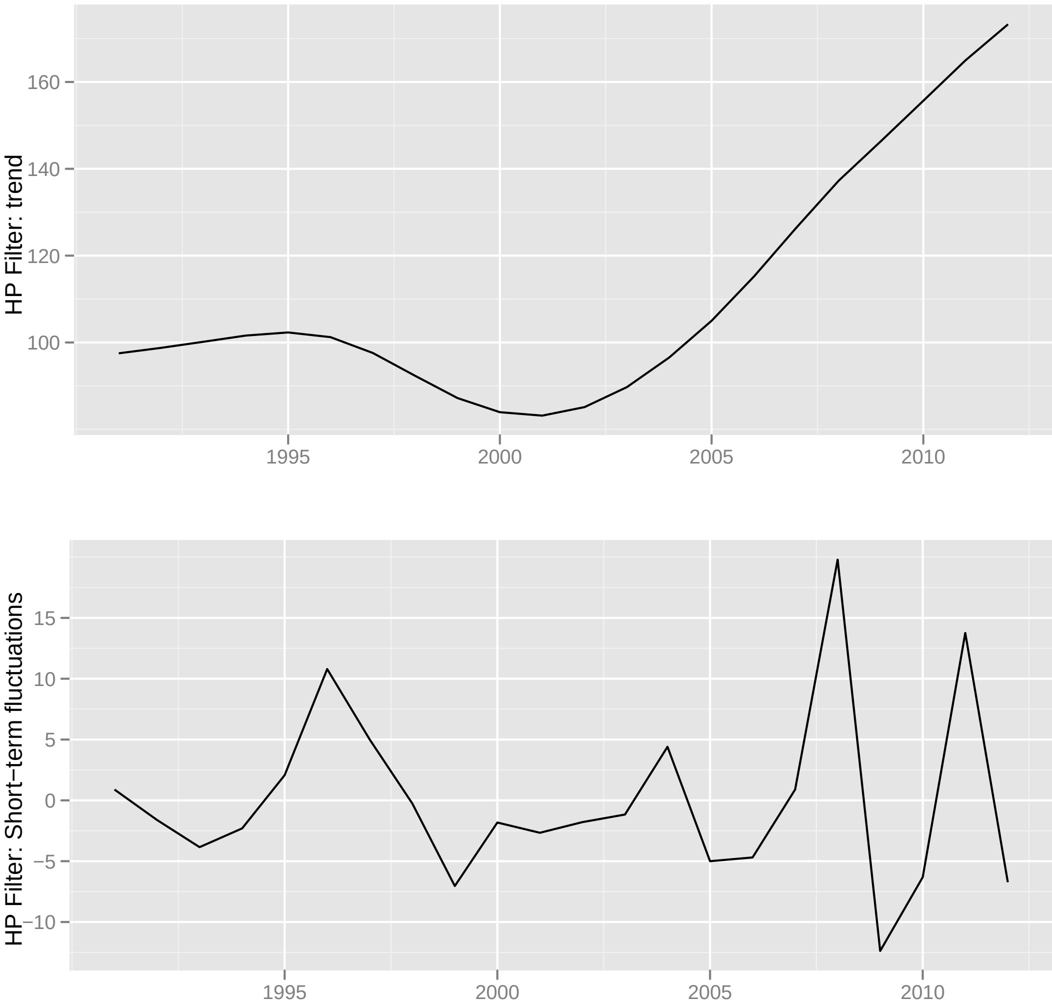
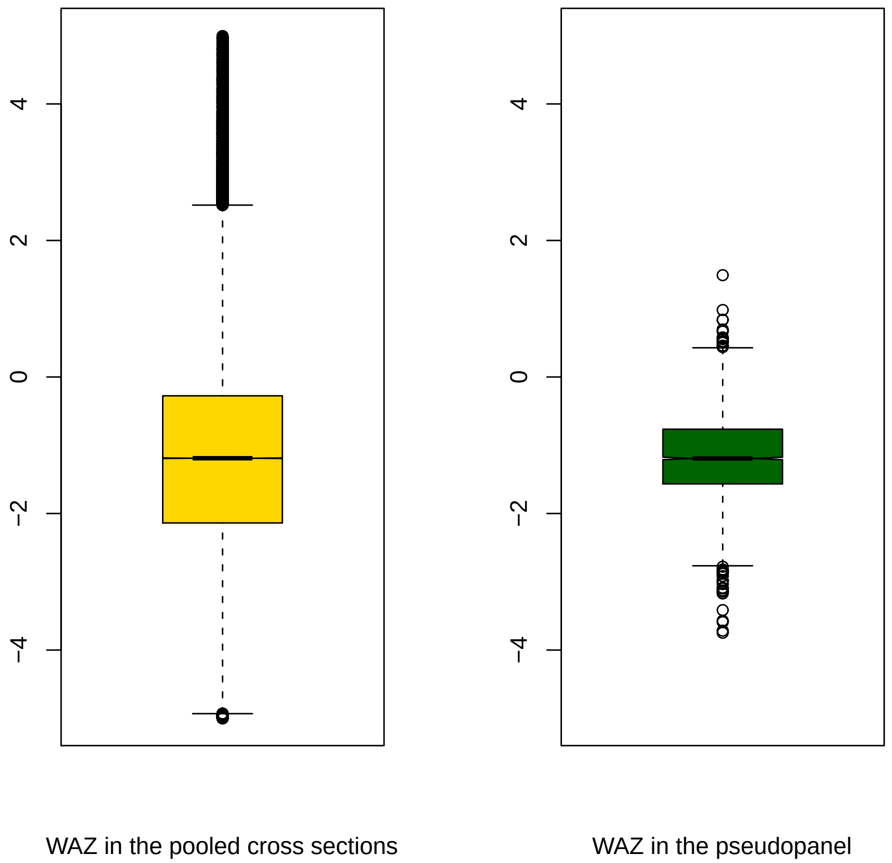


Figure 5: Boxplot of WAZ in pooled cross sections and pseudo panel



6 Discussion of results

In the interpretation of the results, I will rely on the estimates from the Verbeek-Nijman models which, according to Monte Carlo Simulations (MCS, section ??), provide the best performance in terms of bias and random mean squared error for the prevailing pseudo panel set-up. For completeness, the results from the OLS and Fixed Effects models are reported in section .1 and the differences in the results are discussed.

The results of the EIV models 1 to 7 are summarized in Table 5. From model 1, we learn that the overall price index has a negative and significant effect on child health. The coefficient estimate of -0.0008 seems small at first glance but appears considerably strong when set in relation to the recent hike in food prices and the effect of the other variables. In the year 2000, the food price index was at about 82 and increased thereafter to 149 in 2010 – an increase in food prices by 82 per cent. It corresponds to a mean reduction of cohort WAZ by 0.05 standard deviations (SD) and an increase in prices in this magnitude could offset the positive effect of 3.44 additional years of maternal education. Given that we are considering average cohort effects, the effect on the most vulnerable individuals of any given cohort is likely to be considerably stronger. To illustrate this point, consider that the WAZ in the population of children has mean -1.19 with standard deviation 1.43. In the cohort population, the mean of the WAZ is identically at -1.19, but the overall standard deviation is reduced to 0.59 (see Figure 5). Due to the higher variation in the child population, it is more likely to find stronger effects for some individuals which can be obscured when effects on cohort means are considered.

Furthermore, child health is a conservative measure of the change in household welfare: households can employ various coping strategies to buffer the effect of an increase in food prices. Only if the negative shock to household welfare is strong enough, will it also translate in a changed health status of children. Given the strong effect on child health, it is likely that other aspects of household welfare are also strongly affected by the increase in food prices.

From the model with the overall food price index, we have learned that fluctuations in food prices have an economically significant effect on household welfare. In the next step, I attempt to decompose this effect and analyze to which component of price variation this effect can be attributed. To do so, I decompose the food price indicator in the following indicators: Coefficient of Variation, price change in per cent, HP Filter, HP Trend, period of sustained increases in prices and period of sustained decreases in prices.

From the monthly information on the food price index provided by the IMF, I calculate a Coefficient of Variation (CoV) which captures the month-to-month volatility in food prices. Increases in this month-to-month volatility seem to translate into worsened child health status (model 2)– which implies that the households were not able to hedge against this volatility. The Coefficient of Variation ranges between 1.5 and 13.8 with maximum volatility in 2008. The median CoV is 4.27 which corresponds to a reduction in WAZ by 0.02 – the effect size of 1.1 year of maternal education. In the case of extreme volatility, the year 2008, the effect corresponds to a reduction in WAZ by 0.05 which again corresponds to 3.6 years of maternal education and is a large effect given that it corresponds to the volatility within only one year.

Model 7 shows how the year-to-year change in prices relates to WAZ. The indicator is defined as percentage change in the food price index from one year to the next. The point estimate of -0.13 suggests a negative and significant impact of price changes on WAZ. A price increase by 6 per cent – the median change during the period of observation – is equivalent to the effect of -0.5 years of female education. The most extreme observed price increase of 20 per cent corresponds to the effect size of 1.8 years of education. Given that the price measure relates to the change in prices from one year to the next, the effect size can be considered strong.

In a next step, I decompose the IMF's food price index in a trend (model 4) and short term fluctuation around the trend (model 3 in Table 5) using a Hodrick-Prescott (HP) filter. This exercise can be informative of whether the negative effect of price variation on households is transmitted through permanent shocks (trend) or transitory shocks (short-term fluctuation around the trend). Despite their widespread application, HP filters are controversial among macroeconomists and the results should therefore be interpreted with caution.[39] From model 3, we see a negative and significant coefficient estimate for the HP trend.[40] This result indicates that permanent shocks on food prices do have a negative effect on household welfare. The negative effect of the trend is economically significant in the medium term. When considering the increase in the food price level from the trend decomposition, the food price level increased from 83 in 2000 to 156 in 2010 which corresponds to a decrease in child WAZ by 0.07 SD or the equivalent effect of -4.8 years of maternal education.

However, the decomposition in trend and short-term fluctuation does not offer conclusive evidence on the effect of transitory shocks (model 4), as the coefficient estimate is negative but not significant. With respect to the latter result, there seem two possible explanations: First, transitory shocks indeed do not affect household welfare negatively. Second, the HP

[39] One practical issue concerns the choice of the smoothing parameter λ. The higher λ, the smoother the trend. Following Ravn and Uhlig (2002), I choose $\lambda = 6.25$ for the price index with annual frequency.

[40] The result is invariant to estimating a joint specification which contains both variables at the same time.

decomposition does not leave sufficient variation in the HP filter variable to yield significant estimates. Taking into account the negative coefficient estimates on the CoV and the percentage change from one period to another, the second explanation seems plausible.

Finally, I consider the effect of sustained periods of price increases (model 5) and decreases (model 6) which are defined as a minimum of two subsequent price changes in the same direction. Strikingly, sustained increases in prices do strongly and negatively affect child health while sustained decreases in prices have no significant effect on child health. Living through an episode of sustained increases in prices decreases WAZ by 0.05 – this corresponds to the effect of 3.5 years of maternal education. The insignificant and small coefficient on periods of price decreases could indicate that decreases in prices are not transmitted to households to the same extent than increases in prices. This interpretation is in line with previous evidence on price pass-through (Morisset, 1998).

The overall negative relationship between food price variation and child health, which we observe when considering the effect of the food price index on child WAZ in model 1, seems to operate through volatility (model 2), short-term changes in prices (model 7) and permanent shocks in (model 4). Periods of sustained increases in prices (model 5) also have a negative impact on WAZ. No significant effect of the short-term fluctuation and sustained periods of price decreases could be identified.

Table 5: Summary of results - Errors-in-variables models (1) to (7).

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	-0.00077	-0.0039	-6e-04	-0.001	-0.053	0.0094	-0.13
	(0.00013)**	(0.0011)**	(0.00039)	(0.00016)**	(0.0058)**	(0.011)	(0.036)**
Impr. ws.	-0.039	-0.042	-0.046	-0.035	-0.07	-0.046	-0.049
	(0.021)*	(0.021)*	(0.021)**	(0.021)	(0.021)**	(0.022)**	(0.021)**
Impr. san.	0.13	0.12	0.13	0.14	0.091	0.13	0.12
	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**
Agr. empl.	-0.11	-0.087	-0.097	-0.12	-0.1	-0.1	-0.1
	(0.024)**	(0.025)**	(0.025)**	(0.024)**	(0.024)**	(0.025)**	(0.024)**
Agr. self-empl.	-0.14	-0.13	-0.13	-0.15	-0.13	-0.13	-0.13
	(0.017)**	(0.016)**	(0.016)**	(0.017)**	(0.016)**	(0.016)**	(0.016)**
Wealth	0.059	0.062	0.062	0.056	0.057	0.059	0.058
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**
Female educ.	0.015	0.016	0.015	0.013	0.017	0.015	0.016
	(0.0062)**	(0.0063)**	(0.0063)**	(0.0062)**	(0.0062)**	(0.0063)**	(0.0063)**
Urban	0.065	0.077	0.081	0.062	0.12	0.087	0.095
	(0.042)	(0.042)*	(0.042)*	(0.042)	(0.042)**	(0.042)**	(0.042)**
Male educ.	0.024	0.022	0.02	0.025	0.017	0.021	0.021
	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**
GDP	0.095	0.07	0.048	0.1	0.058	0.036	0.054
	(0.031)**	(0.031)**	(0.03)	(0.031)**	(0.03)**	(0.03)	(0.03)*
Time trend	0.0065	0.0059	0.0052	0.0071	0.0065	0.0054	0.0064
	(9e-04)**	(0.00089)**	(0.00087)**	(0.00091)**	(0.00087)**	(0.00091)**	(0.00093)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

After considering the results regarding food prices, I briefly discuss the control variables. As suggested by the development literature (Charmarbagwala et al., 2004), maternal and paternal education both have a positive effect on child health. The effect of an additional year of paternal or maternal education increases WAZ by approximately 0.02 SD. The WAZ of a child whose both parents received primary education[41] as compared to a child whose parents did not receive primary education would be 0.2 SD higher – this corresponds to 69 per cent of a within-cohort standard deviation in child WAZ. When interpreting results based on the pseudo panel, we should keep in mind that the interpretation of some variables may change compared to a cross sectional set-up, as coefficients are identified through the cohort-level variation in the variables over time. For instance, this changes the usual meaning of the coefficient of the "urban" variable – household resides in an urban area – to urbanization over time. Table 5 indicates mixed

[41]The mean primary school duration in low and middle income countries is six years, according to the UNESCO Institute for Statistics (Source: World Bank Development Indicators, http://data.worldbank.org/indicator/SE.PRM.DURS, July 19, 2013).

evidence for urbanization: the parameter is estimated positive and significant only in some of the specifications.

As expected, wealth has a positive and significant effect on child health. The results on GDP per capita growth are mixed: Some coefficients are estimated significant while others are not. This is due to the inclusion of a global time trend in all specifications which captures a general positive trend in macroeconomic variables, including GDP per capita[42]. Both wealth (here: measured as an asset-based index) and GDP per capita are variables which usually change only slowly with time – this is reflected by the relatively low within standard deviations of the variables. For this reason, it is informative to interpret the respective effect size with reference to their within-cohort standard deviations. The increase of the wealth index by one within-cohort standard deviation (0.42) increases WAZ by 0.03 SD. An increase of one within-SD of GDP (0.13) is estimated to increase child WAZ by approximately 0.01 SD. The time trend has a positive and significant relation with WAZ. Each year, the arithmetic mean of the WAZ increases by approx. 0.006 SD. This reflects a general positive trend in child health status for the countries in the sample. The statistical and economic significance of the time trend confirms the necessity to include such a term in the specification; without the time trend, this positive development would have been absorbed by the HP trend whose coefficient estimate turns out positive and significant if the time trend is omitted.

Agricultural employment and agricultural self-employment is strongly and negatively correlated with child health; this does not come as a surprise. Agricultural wage employment is a low-wage, low-skill sector in most developing countries in which workers typically lack productive assets such as land. From Table 5 we take that the negative association of the self-employed with child WAZ of -0.14 is even more pronounced, indicating that the agriculturally self-employed, are even worse off.

Finally, access to safe drinking water and adequate sanitation has been shown to be an important determinant of child health in the literature (Fewtrell et al., 2005; Charmarbagwala et al., 2004; Waddington et al., 2009). Indeed, we observe a strong and positive effect of access to improved sanitation technologies on WAZ. If a cohort which previously did not have access to adequate sanitation gains access, child WAZ increases by 0.12. Surprisingly, access to improved water supply technologies is negatively correlated with child health; the correlation is not significant in model (3) and marginally significant in models (1) and (2). This weak but counter-

[42] If the global time trend is omitted, GDP per capita is always significant. However, in this essay, we are not concerned with estimating the effect of GDP per capita on child health – GDP per capita is rather included as a control variable. The time trend is kept in all specifications to ensure that the results are not driven by general trend in macroeconomic variables.

intuitive result may be explained by shortcomings of the applied definition (type of infrastructure proxies water quality) and ambiguous codes of water technologies in the DHS data (see section on data and definitions). Günther and Fink (2010) proposed an alternative definition for water technologies which comprises the three categories of basic water technology, advanced water technology and a baseline category which contains surface water. When the model is re-estimated with this definition, the coefficients on advanced water technologies remain negative but are no longer significant while the coefficient on basic water supply technologies remains negative and significant. To conclude the discussion of controls, apart from the result on water supply, the relation between WAZ and the control variables is in line with theoretical expectations.

6.1 How the results compare with other estimators

The OLS estimates (see section .1) differ considerably from the results of the EIV models. We notice differences in the coefficients and precision of estimation for some of the control variables (especially: improved sanitation, agricultural self-employment, urban, GDP and trend). More interestingly, also the estimates of the food price indicators are affected. The food price index, trend in food prices and percentage change in prices are negatively correlated with child health. The coefficient on the CoV, episodes of sustained increases and decreases in food prices and HP filter are positively associated with child health – which contradicts theoretical expectations and the OLS results on the price index and trend; given that there is a negative effect of the food price index, trend and percentage change in prices, we would expect an opposite sign for the coefficient on episodes of price increases. I take this as an indication that the OLS results might not be reliable.

The application of OLS seems inadequate for an econometric and a conceptual reason. First, OLS cannot control for time-invariant unobserved heterogeneity at the household level which may play a role in mediating between food prices and child health. The OLS approach exploits the between-individual variation (as well as variation over time) to identify the effect of the variables. The food price data is common to all individuals at a given time such that, abstracting from mediating characteristics, there should be no differential impact on child health. The between-variance at a given time, which drives the difference in results to the pseudo panel approach, must then be explained by other factors than food prices. Second, regarding the question how food prices affect child health, we are not interested in identifying an association of food prices and child health between different individuals but rather how food prices affect health over time. For these two reasons, an approach which exploits only variation over time seems more adequate.

Finally, the fact that some of the results differ considerably implies that Fixed Effects do matter for the issue under question and should not be disregarded.

The results from the Fixed Effects model (see .1) and the EIV model resemble each other closely, but some differences can be noticed. The coefficients on all food price indicators (except sustained periods of price decreases) have the same signs as in the EIV model but differ in the magnitude and standard errors. The estimates of the controls have mostly the same signs but differ somewhat in magnitude and standard errors. The coefficient on male education is reversed in signs for models 2, 3, 5, 6 and 7. Here the coefficient estimate on male education appears negative but not significant. The estimates for GDP and improved water supply are also insignificant. Against the background of the MCS results, the differences do not come as a surprise. The Fixed Effects model does not make use of all of the available information: it does neither weight the observations by their accuracy (all pseudo individuals contribute equally to the fit) nor does it correct for measurement error. Furthermore, the MCS indicated that standard errors are estimated incorrectly in the FE model in the presence of measurement error – shedding doubts on the validity of inference based on the FE model.

Overall, the EIV model seems to be the appropriate choice from an econometric perspective. The MCS in section **??** suggests its better performance in terms of bias, root mean square error and accuracy of the standard errors. In addition, the EIV results seem plausible against the theoretical background. For these reasons, in the above discussion of the results, I rely on the EIV model.

6.2 Food prices and underweight

In this section, the previous EIV-models are re-estimated so that the dependent variable WAZ is replaced by a binary variable which indicates child underweight and severe child underweight respectively. In the anthropometric literature, children with a WAZ below -2 (i.e. two standard deviations below the median of the reference population) are defined as underweight and children with a WAZ below -3 severely underweight. In the cohort model, the variables underweight and severe underweight indicate the percentage of children who fall below the respective threshold. The coefficient estimates, then, can be interpreted as the per cent of children who fell below / or rose above those respective thresholds due to the variation in food prices. If the previous results are economically meaningful, we should observe the opposite signs on all coefficient estimates. The effect size and level of significance of the estimates may differ as it depends on the distribution of children around the respective thresholds.

The below tables report the coefficient estimates of the altered model. The results prove robust to this change in definition. All coefficient estimates show the opposite sign compared to the previous model – this corresponds to the same direction of effect. Different to the original model, the coefficient estimate on the HP filter is now significant, i.e. the short-term fluctuation in prices does increase child malnutrition.

Table 6: Food prices and underweight ($WAZ < -2SD$)

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	0.00023 (3.9e-05)**	0.0016 (0.00032)**	3e-04 (0.00011)**	0.00029 (4.7e-05)**	0.0096 (0.0017)**	-0.0011 (0.0033)	0.032 (0.01)**
Impr. ws.	0.0012 (0.0062)	0.0018 (0.0062)	0.0035 (0.0062)	0.00034 (0.0062)	0.0076 (0.0063)	0.0033 (0.0063)	0.0042 (0.0063)
Impr. san.	-0.03 (0.006)**	-0.026 (0.006)**	-0.028 (0.006)**	-0.032 (0.006)**	-0.023 (0.0061)**	-0.03 (0.006)**	-0.028 (0.006)**
Agr. empl.	0.019 (0.0071)**	0.011 (0.0072)	0.015 (0.0072)**	0.022 (0.0071)**	0.018 (0.0071)**	0.018 (0.0071)**	0.018 (0.0071)**
Agr. self-empl.	0.028 (0.0048)**	0.023 (0.0048)**	0.023 (0.0048)**	0.029 (0.0048)**	0.023 (0.0048)**	0.023 (0.0048)**	0.024 (0.0048)**
Wealth	-0.02 (0.0045)**	-0.021 (0.0045)**	-0.021 (0.0046)**	-0.019 (0.0045)**	-0.02 (0.0045)**	-0.02 (0.0046)**	-0.02 (0.0046)**
Female educ.	-0.00024 (0.0018)	-0.00066 (0.0018)	-0.00062 (0.0018)	8.8e-05 (0.0018)	-0.00074 (0.0018)	-3e-04 (0.0018)	-0.00052 (0.0018)
Urban	-0.02 (0.012)	-0.023 (0.012)*	-0.024 (0.012)**	-0.019 (0.012)	-0.033 (0.012)**	-0.026 (0.012)**	-0.028 (0.012)**
Male educ.	-0.0056 (0.0017)**	-0.0052 (0.0017)**	-0.0045 (0.0017)**	-0.006 (0.0017)**	-0.004 (0.0017)**	-0.0046 (0.0017)**	-0.0047 (0.0017)**
GDP	-0.032 (0.0091)**	-0.028 (0.009)**	-0.019 (0.0088)**	-0.032 (0.0091)**	-0.019 (0.0087)**	-0.015 (0.0088)*	-0.019 (0.0087)**
Time trend	-0.0025 (0.00026)**	-0.0024 (0.00026)**	-0.0021 (0.00025)**	-0.0027 (0.00027)**	-0.0023 (0.00026)**	-0.0021 (0.00026)**	-0.0024 (0.00027)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Per cent of children underweight. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

Table 7: Food prices and severe underweight ($WAZ < -3SD$)

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	0.00014	0.0012	4e-04	0.00013	0.0074	-0.0034	0.027
	(2.6e-05)**	(0.00022)**	(7.8e-05)**	(3.2e-05)**	(0.0012)**	(0.0022)	(0.0072)**
Impr. ws.	0.0075	0.0077	0.0092	0.0074	0.012	0.009	0.0096
	(0.0043)*	(0.0043)*	(0.0043)**	(0.0043)*	(0.0043)**	(0.0043)**	(0.0043)**
Impr. san.	-0.011	-0.0084	-0.0089	-0.012	-0.0058	-0.012	-0.0098
	(0.0041)**	(0.0041)**	(0.0041)**	(0.0041)**	(0.0042)	(0.0041)**	(0.0041)**
Agr. empl.	0.017	0.011	0.012	0.018	0.016	0.017	0.016
	(0.0049)**	(0.0049)**	(0.0049)**	(0.0049)**	(0.0048)**	(0.0049)**	(0.0049)**
Agr. self-empl.	0.023	0.021	0.021	0.023	0.021	0.021	0.022
	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**
Wealth	-0.008	-0.0087	-0.0093	-0.0077	-0.0078	-0.0079	-0.0077
	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**
Female educ.	0.0012	0.00091	0.00075	0.0014	0.00084	0.0012	0.00099
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Urban	-0.023	-0.024	-0.025	-0.023	-0.032	-0.027	-0.028
	(0.0083)**	(0.0083)**	(0.0083)**	(0.0083)**	(0.0083)**	(0.0084)**	(0.0083)**
Male educ.	-0.003	-0.0029	-0.0022	-0.0031	-0.002	-0.0024	-0.0025
	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)*	(0.0011)**	(0.0011)**
GDP	-0.031	-0.03	-0.026	-0.029	-0.023	-0.02	-0.024
	(0.0062)**	(0.0062)**	(0.006)**	(0.0062)**	(0.0059)**	(0.006)**	(0.006)**
Time trend	-0.0016	-0.0016	-0.0013	-0.0016	-0.0016	-0.0015	-0.0016
	(0.00018)**	(0.00018)**	(0.00017)**	(0.00018)**	(0.00017)**	(0.00018)**	(0.00018)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Per cent of children severely underweight. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$
Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

The results provide insights as to how food price shocks have affected the rates of underweight and severe underweight children. For the sake of comparison, the same examples are given as in the previous analysis. The observed increase in the food price index from 82 to 149 results in an increase of child underweight by 1.5 percentage points and in an increase of severe underweight by 1 percentage point. While the observed median CoV results in an increase of 0.7 percentage points in underweight and 0.5 percentage points in severe underweight, the highest observed CoV of 13.8 results in an increase of underweight by 2.2 percentage points and severe underweight 1.7 percentage points respectively. The latter increase in the rate of underweight children appears strong considering that it relates to the effect of the month-to-month variation during a single year. The annual change in prices in per cent of previous year's prices also have a positive effect on the rate of malnourishment. While a median price increase (6 per cent) leads to an increase both in malnutrition and in severe malnutrition by 0.2 percentage points, the most extreme price change (21 per cent) leads to an increase in malnutrition of 0.7 and 0.6 percentage points respectively. Again, given that this impact concerns only the price change from one year to the next, the effect size is considerably strong. As a next step, the fluctuation around the trend versus the effect of the trend itself is considered. The deviation from the trend – 19.79 index points in the most extreme year (2011) – results in an increase of 0.6 percentage points in underweight and 0.8 percentage points in severe underweight. As previously, the trend in food prices has a negative impact on child health: the increase in trend from 83 to 156 results in an estimated increase of underweight by 2.1 percentage points and an increase in severe underweight by 1 percentage point. Finally, episodes of subsequent increases in prices lead to an increase of approximately 1 percentage point in underweight and 0.7 percentage points in severe underweight. As before, episodes of subsequent decreases in prices have no significant impact.

In sum, the above results underline the robustness of the previous findings. Beyond this, the models provide further insights into how the rates of underweight and severely underweight children changed due to observed variation in food price changes. Even though the latter illustrates the economic significance of the issue, the practical relevance of whether a child falls just below or above the threshold is not clear. Eventually, coefficient estimates depend on the prevalent distribution of children around the respective thresholds and do not capture the effect on the entire population.

6.3 Robustness of results to choice of food price index

In this section, I test whether these results are sensitive to the choice of food price index. In re-estimating the above models, I substitute the IMF's food price index with the food price index[43] of the World Bank's GEM Commodities' database[44]. There are some differences between the two indices with respect to the choice and relative weights of commodities in these baskets. However, overall, both approaches aim to capture "global food prices" and the estimation should yield similar results.

One may also debate whether it is more appropriate to use a food price index in nominal or real terms. In the previous analysis, I rely on a food price index in nominal terms; using a food price index in real terms would require an appropriate deflator. However, it is not obvious which deflator is the appropriate choice to deflate a global food price index. The application of a deflator changes the price series and, if an inappropriate deflator is chosen, may conflate the results with other phenomena related to inflation in the basket of goods of the reference population, usually a typical US household. Against this background, choosing any deflator comes with the risk of introducing bias to the estimation and making the results less credible

[43]The year 2005 corresponds to an index value of 100. Hence, the choice of the reference year is identical in both price indices.

[44]Source: http://data.worldbank.org/data-catalog/commodity-price-data, site visited: Nov 2, 2013.

instead of more credible. Von Braun and Tadesse (2012) argue that "comparisons of real values that rely on middle classbased US$ deflators are misleading, as they do not reflect the food basket of the poor." Nevertheless, as an additional robustness check, I also substitute the IMF's nominal food price index with the World Bank's food price index in real terms.[45]

The results of this exercise are reported in Table 8. Given that the three food price indices differ in their range and variation, it is difficult to directly compare the effect size of the coefficient estimates. For this reason, I also report the effect sizes in relation to maternal education and with respect to malnutrition to add an economic meaning to the interpretation. Table 8 indicates that, overall, the results prove robust to using the World Bank's nominal and real food price indices. For the Food Price Index, the Coefficient of Variation, the HP Trend and Price Hikes, we only observe minor differences between the three models. The coefficient estimates on the percentage change in prices show the same sign in all three models but the effect is noticeably more pronounced for the models based on the World Bank's index.

Two differences in the results can be noticed: first, the coefficient estimate on the HP Filter with respect to changes in WAZ is now significant for both of the World Bank's price indices. While a median deviation from the trend only has a negligible effect on child WAZ, the effect size of the most extreme deviation from trend corresponds to the effect of -2 to -3.7 years of education and to a 1 to 1.4 per cent increase in malnutrition. Even though this economically-significant effect could not been detected with the IMF's index, it is in line with the overall results of this analysis. Second, sustained falls in prices do improve child health and decrease child malnutrition in the models based on the World Bank's food price indices. This result counters the finding that only upwards movements in prices are transmitted to domestic markets (Morisset, 1998).

[45]The real price series is denoted in 2005 real US$.

Table 8: Summary of results, IMF and WB food price indices

	Dependent variable: weight-for-age z-score		Dependent variable: Malnutrition ($WAZ < -2SD$)	
	Coefficient	Effect size compared to mother's education	Coefficient	Effect of observed price change
Food Price Index (FPI)		(Change in FPI from 2000 to 2010)		(Change in FPI from 2000 to 2010)
IMF, nominal USD	-0.008**	-3.5 years	0.00023**	+1.5%
WB, nominal USD	-0.0006**	-3.7 years	0.00018**	+1.7%
WB, real USD	-0.0011**	-4.7 years	0.00032**	+2.1%
Coefficient of Variation		(Median CoV, Max. CoV)		(Median CoV, Max. CoV)
IMF, nominal USD	-0.0039**	-1.1 years, -3.6 years	0.0016**	+0.7%, +2.2%
WB, nominal USD	-0.003**	-0.9 years, -3.3 years	0.0011**	+0.5%, +1.8%
percentage Change in FPI		(Median Change, Max. Change)		(Median Change, Max. Change)
IMF, nominal USD	-0.13**	-0.5 years, -1.8 years	0.032**	+0.2%, +0.7%
WB, nominal USD	-0.19**	-0.9 years, -3.7 years	0.043**	+0.3%, +1.2%
WB, real USD	-0.17**	-0.3 years, -2.5 years	0.054**	+0.2%, +1.2%
HP Filter		(Median deviation, Max. deviation)		(Median deviation, Max. deviation)
IMF, nominal USD	-0.0006	not significant	0.0003**	0%, +0.6%
WB, nominal USD	-0.001**	+0.2 years, -2 years	0.0003**	0%, +1.0%
WB, real USD	-0.0027**	-0.01 years, -3.7 years	0.0007**	0%, +1.4%
HP Trend		(Change in HP Trend from 2000 to 2010)		(Change in HP trend from 2000 to 2010)
IMF, nominal USD	-0.001**	-4.8 years	0.00029**	+2.1%
WB, nominal USD	-0.0007**	-4.6 years	0.0002**	+2.0%
WB, real USD	-0.0011**	-4.7 years	0.0003**	+2.1%
Price Hikes		(Living through a period of increasing prices)		(Living through a period of increasing prices)
IMF, nominal USD	-0.053**	-3.5 years	0.0096**	+1.0%
WB, nominal USD	-0.061**	-4.1 years	0.011**	+1.1%
WB, real USD	-0.062**	-4.1 years	0.012**	+1.2%
Price Drops		(Living through a period of decreasing prices)		(Living through a period of decreasing prices)
IMF, nominal USD	0.0094	not significant	-0.0011	not significant
WB, nominal USD	0.097**	+6.5 years	-0.015**	-1.5%
WB, real USD	0.095**	+6.3 years	-0.016**	-1.6%

Robustness test with three Food Price Indices: 1) International Monetary Fund's (IMF) index in nominal USD, 2) the World Bank's (WB) Food Price Index in nominal USD, 3) The World Bank's Index in real USD. Comparison of coefficient estimates, effect sizes in education equivalent and effect on malnutrition. The reference experiment is indicated in parentheses. Dependent variable indicated in first row. Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005. * $p < 0.05$, ** $p < 0.01$.

6.4 Robustness of results to cohort definition

The critical reader may wonder how robust the previous results are with respect to varying the cohort definition of the synthetic panel. To dispel doubts, I run the models (1) to (7) with WAZ as dependent variable on various cohort definitions. Cohorts are constructed according to the procedure described in section 4 whereby the minimum density per cohort is varied from 10 per cent to 0.25 per cent. This results in synthetic panels with 628 to 5045 observations. Table 11 lists the cohort sizes and corresponding per centiles in the respective synthetic panel. The results are reported in section .2. The coefficient estimates and level of significance prove robust to varying cohort definitions. In line with the results of the MCS, the standard errors slightly increase as the number of cohorts decreases.

7 Conclusion

The recent surge in food prices and volatility has received much attention from policy makers, academia, and the general public. In academia, much of the literature on the consequences of these recent food price hikes focuses on the effect of high food prices in specific regional and time contexts. This essay contributes to this fast-growing literature by disentangling the effect of food price variation on household welfare, extending the regional and time perspective, and by applying a methodology which has not been used to examine this question before.

To attribute the welfare effects to short-, medium- and long-term variation in prices, I decompose three food price indices by the International Monetary Fund and the World Bank in percentage change in prices from one period to the next, a Coefficient of Variation, HP Filter and Trend, as well as episodes of sustained hikes and drops in prices. To identify the effect of these price series on household welfare, proxied by the child weight-for-age z-score, I rely on a pseudo panel approach which allows me to exploit information from repeated cross sections of the Demographic and Health Surveys on approximately 500,000 children from 38 countries over a period of 20 years. Instead of following individuals over time as in standard panel approaches, in this approach, birthyear-cohorts are followed over time. To remedy potential bias due to sampling error, the Verbeek-Nijman (1992) estimator, a variant of the Deaton's (1985) EIV model, is applied. This estimator has been shown to perform best in the context of the prevalent data situation using Monte Carlo Simulation techniques.

I find that increases in the overall food price index have a negative impact on household welfare. The effect size is economically significant: when compared to the effect size of maternal education, the observed price increase from the year 2000 to 2010 would offset the positive effect of 3.5 years of maternal education. It is also illustrative to calculate the effect in terms of child malnutrition rate (children who fall below a WAZ < -2 SD): the price increase over the same period leads to a 1.5 per cent increase in the rate of child malnutrition in the countries sampled.

Decomposing the index in the above components, I find that this negative effect operates through volatility, as measured by the CoV, the change in prices from one period to another, the HP trend and episodes of sustained increases in prices. The effects can be considered strong when set in relation to maternal education and malnutrition. The effect of price volatility (CoV) in the year 2008 on child WAZ corresponds to -3.6 years of maternal education and an increase in malnutrition by 2.2 per cent. Given that this effect refers to only one year, the effect size can be considered high. Contrary to the CoV, the impact of the HP Trend materializes over a rather long period of time: the increase in HP Trend from 2000 to 2010 is equivalent to the effect of -4.8 years of maternal education and translates in an increase of malnutrition by 2.1 per cent. Living through a period of continued price increases[46] corresponds to the effect of -3.5 years of education or a 1 per cent increase in malnutrition.

There is mixed evidence on the impact of the short-term fluctuation around a trend (HP Filter) and whether continued decreases in prices improve child health. While the coefficient estimates based on the IMF's nominal food price index are insignificant, the estimates based on the World Bank's index in both nominal and real terms are significant. According to the latter results, the variation in the HP Filter has a negative relation with child WAZ: the effect of the maximum deviation from trend in the year 2008 corresponds to -2 years of maternal education and implies an increase in malnutrition by 1 per cent. Based on the World Bank data, periods of subsequent drops in food prices seem to improve child health: the effect size corresponds to 6.5 years of maternal education, or a 1.5 per cent decrease in malnutrition.

To summarize, I find that, overall, there is a negative relationship between the variation in global food prices and household welfare. The effect is transmitted through short-term price movements (volatility), medium-term changes (period-to-period change, HP Filter) and permanent shocks to global food prices (HP trend, price hikes). The effects on household welfare are strong considering equivalent education effects and estimated effects of the above indicators on malnutrition rates.

[46] Periods of continued price increases are defined as two or more subsequent upward movements in prices. Periods of sustained drops in prices are defined analogously.

Finally, I would like to point to an avenue for future research: the above analysis abstracts from heterogeneous impacts which go beyond the scope of this essay. Heterogeneous impacts could be analyzed at different levels of aggregation. At the country level, the status of a country as a net importer (or exporter) of agricultural goods in relation to total GDP, the pass-through of international food prices to domestic markets as well as the presence (or absence) of social and economic institutions could be determinants of impact heterogeneity. At the household level, factors may include the position of the household as net seller vs. net buyer, wealth, formal and informal insurance and access to credit. This is by no means an exhaustive list of potential factors according to which heterogeneous effects may materialize. Detecting impact heterogeneity at different levels of aggregation, including the country and household level, but potentially also in-between levels such as regions or districts, is an interesting and important avenue for further research which could be addressed in the framework of a pseudo panel approach.

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.1 Results from OLS and Fixed Effects models

Table 9: Ordinary Least-Squares (OLS) Estimator.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Food Price	-0.000419**	0.0116**	0.00436**	-0.00145**	0.0401**	0.0578**	-0.336**
	(0.0000958)	(0.000737)	(0.000264)	(0.000116)	(0.00402)	(0.00767)	(0.0283)
Impr. ws.	-0.0424**	-0.0403**	-0.0421**	-0.0420**	-0.0427**	-0.0440**	-0.0439**
	(0.00468)	(0.00468)	(0.00467)	(0.00468)	(0.00468)	(0.00468)	(0.00471)
Impr. san.	0.0193**	0.0218**	0.0208**	0.0222**	0.0228**	0.0194**	0.0125*
	(0.00519)	(0.00519)	(0.00519)	(0.00520)	(0.00521)	(0.00519)	(0.00523)
Agr. empl.	-0.107**	-0.111**	-0.109**	-0.107**	-0.106**	-0.107**	-0.106**
	(0.00457)	(0.00458)	(0.00458)	(0.00457)	(0.00457)	(0.00457)	(0.00463)
Agr. self-empl.	0.0627**	0.0629**	0.0651**	0.0624**	0.0635**	0.0643**	0.0634**
	(0.00313)	(0.00312)	(0.00313)	(0.00313)	(0.00313)	(0.00313)	(0.00315)
Wealth	0.124**	0.125**	0.125**	0.123**	0.125**	0.125**	0.125**
	(0.00172)	(0.00171)	(0.00171)	(0.00172)	(0.00171)	(0.00171)	(0.00173)
Female educ.	0.0265**	0.0261**	0.0261**	0.0266**	0.0263**	0.0263**	0.0263**
	(0.000616)	(0.000615)	(0.000615)	(0.000615)	(0.000615)	(0.000615)	(0.000620)
Urban	0.0411**	0.0411**	0.0433**	0.0415**	0.0417**	0.0414**	0.0405**
	(0.00508)	(0.00508)	(0.00508)	(0.00508)	(0.00508)	(0.00508)	(0.00512)
Male educ.	0.0168**	0.0164**	0.0166**	0.0168**	0.0167**	0.0168**	0.0168**
	(0.000552)	(0.000552)	(0.000552)	(0.000552)	(0.000552)	(0.000552)	(0.000556)
GDP	0.194**	0.190**	0.192**	0.196**	0.192**	0.193**	0.195**
	(0.00252)	(0.00251)	(0.00251)	(0.00251)	(0.00251)	(0.00251)	(0.00253)
Time trend	-0.00843**	-0.0130**	-0.0103**	-0.00550**	-0.0104**	-0.00897**	-0.00611**
	(0.000464)	(0.000417)	(0.000363)	(0.000493)	(0.000367)	(0.000374)	(0.000471)
Constant	-2.514**	-2.533**	-2.520**	-2.452**	-2.535**	-2.545**	-2.570**
	(0.0178)	(0.0170)	(0.0171)	(0.0183)	(0.0170)	(0.0171)	(0.0173)
Observations	497839	497839	497839	497839	497839	497839	489965

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

OLS estimation

Table 10: Efficient Wald / Fixed Effects Estimator.

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Food Price	-0.00170**	-0.00905**	-0.000972	-0.00230**	-0.0176	-0.0362*	-0.0729
	(0.000275)	(0.00241)	(0.000791)	(0.000331)	(0.0115)	(0.0184)	(0.0654)
Impr. ws.	0.0367	0.0284	0.0187	0.0408	0.0170	0.0210	0.00383
	(0.0358)	(0.0359)	(0.0358)	(0.0358)	(0.0358)	(0.0359)	(0.0361)
Impr. san.	0.138**	0.110**	0.107**	0.152**	0.102**	0.0987**	0.104**
	(0.0367)	(0.0365)	(0.0366)	(0.0369)	(0.0368)	(0.0369)	(0.0369)
Agr. empl.	-0.138**	-0.109**	-0.123**	-0.148**	-0.125**	-0.122**	-0.120**
	(0.0384)	(0.0388)	(0.0386)	(0.0384)	(0.0386)	(0.0386)	(0.0392)
Agr. self. empl.	-0.171**	-0.151**	-0.151**	-0.176**	-0.149**	-0.151**	-0.151**
	(0.0251)	(0.0249)	(0.0250)	(0.0251)	(0.0250)	(0.0250)	(0.0252)
Wealth	0.0887**	0.0949**	0.0939**	0.0874**	0.0927**	0.0967**	0.0890**
	(0.0188)	(0.0188)	(0.0188)	(0.0187)	(0.0189)	(0.0189)	(0.0191)
Female educ.	0.0240**	0.0236**	0.0236**	0.0239**	0.0234**	0.0242**	0.0264**
	(0.00716)	(0.00719)	(0.00720)	(0.00715)	(0.00720)	(0.00721)	(0.00733)
Urban	0.00785	0.0164	0.0160	0.000377	0.0236	-0.000821	0.0317
	(0.0497)	(0.0499)	(0.0500)	(0.0497)	(0.0504)	(0.0505)	(0.0510)
Male educ.	0.00133	-0.0000827	-0.000821	0.00218	-0.000841	-0.000263	-0.00293
	(0.00647)	(0.00649)	(0.00650)	(0.00647)	(0.00650)	(0.00650)	(0.00660)
GDP	0.0655	0.0403	0.00873	0.0769	0.00900	0.0175	-0.0169
	(0.0517)	(0.0518)	(0.0511)	(0.0517)	(0.0511)	(0.0514)	(0.0520)
Time trend	0.00809**	0.00616**	0.00461**	0.00912**	0.00499**	0.00371*	0.00530**
	(0.00152)	(0.00148)	(0.00142)	(0.00155)	(0.00145)	(0.00147)	(0.00157)
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

FE estimation

.2 Robustness: Varying cohort definitions

Table 11: Distribution of cohort size in pseudo panels

	per centile						
Min. Density	5	10	30	50	80	90	95
0.001	4	6	25	55	144	229	324
0.0025	4	7	26	56	146	232	328
0.005	4	8	28	59	148	235	334
0.01	4	9	32	63	154	241	339
0.025	5	11	39	76	176	270	384
0.05	6	14	55	108	258	385	542
0.1	10	25	104	214	514	739	1089
0.25	18	50	249	511	1214	1770	2549

Table 12: Verbeek-Nijman (1993) Estimator, obs. 5045

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	-0.00076	-0.0039	-0.00061	-0.001	-0.053	0.011	-0.13
	(0.00013)**	(0.0011)**	(0.00039)	(0.00016)**	(0.0058)**	(0.011)	(0.036)**
Impr. ws.	-0.038	-0.041	-0.045	-0.035	-0.069	-0.046	-0.049
	(0.021)*	(0.021)*	(0.021)**	(0.021)	(0.021)**	(0.021)**	(0.021)**
Impr. san.	0.13	0.12	0.13	0.13	0.09	0.13	0.12
	(0.02)**	(0.021)**	(0.021)**	(0.02)**	(0.021)**	(0.021)**	(0.021)**
Agr. empl.	-0.1	-0.087	-0.096	-0.12	-0.1	-0.1	-0.1
	(0.024)**	(0.025)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**
Agr. self-empl.	-0.14	-0.12	-0.13	-0.14	-0.12	-0.12	-0.13
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**
Wealth	0.058	0.061	0.061	0.055	0.056	0.058	0.056
	(0.015)**	(0.015)**	(0.016)**	(0.015)**	(0.015)**	(0.016)**	(0.015)**
Female educ.	0.015	0.016	0.016	0.014	0.018	0.015	0.016
	(0.0062)**	(0.0062)**	(0.0062)**	(0.0062)**	(0.0061)**	(0.0062)**	(0.0062)**
Urban	0.073	0.084	0.088	0.07	0.13	0.095	0.1
	(0.041)*	(0.041)**	(0.041)**	(0.041)*	(0.041)**	(0.042)**	(0.041)**
Male educ.	0.023	0.021	0.019	0.024	0.016	0.019	0.02
	(0.0056)**	(0.0056)**	(0.0056)**	(0.0057)**	(0.0056)**	(0.0056)**	(0.0056)**
GDP	0.094	0.069	0.047	0.099	0.057	0.034	0.053
	(0.031)**	(0.031)**	(0.03)	(0.031)**	(0.029)*	(0.03)	(0.03)*
Time trend	0.0066	0.006	0.0052	0.0071	0.0066	0.0056 (9e-	0.0065
	(0.00089)**	(0.00088)**	(0.00086)**	(0.00091)**	(0.00087)**	04)**	(0.00092)**
Observations	5045	5045	5045	5045	5045	5045	4929

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.001

Table 13: Verbeek-Nijman (1993) Estimator, obs. 4979

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	-0.00076	-0.0039	-6e-04	-0.001	-0.053	0.01	-0.13
	(0.00013)**	(0.0011)**	(0.00039)	(0.00016)**	(0.0058)**	(0.011)	(0.036)**
Impr. ws.	-0.038	-0.041	-0.045	-0.035	-0.069	-0.046	-0.049
	(0.021)*	(0.021)*	(0.021)**	(0.021)	(0.021)**	(0.021)**	(0.021)**
Impr. san.	0.13	0.12	0.13	0.14	0.091	0.13	0.12
	(0.02)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**
Agr. empl.	-0.1	-0.086	-0.096	-0.11	-0.1	-0.1	-0.1
	(0.024)**	(0.025)**	(0.025)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**
Agr. self-empl.	-0.14	-0.12	-0.13	-0.14	-0.13	-0.13	-0.13
	(0.016)**	(0.016)**	(0.016)**	(0.017)**	(0.016)**	(0.016)**	(0.016)**
Wealth	0.058	0.06	0.06	0.054	0.056	0.058	0.056
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.015)**	(0.016)**	(0.016)**
Female educ.	0.015	0.016	0.016	0.014	0.018	0.015	0.016
	(0.0062)**	(0.0062)**	(0.0062)**	(0.0062)**	(0.0062)**	(0.0062)**	(0.0062)**
Urban	0.071	0.082	0.086	0.068	0.13	0.093	0.1
	(0.041)*	(0.041)**	(0.041)**	(0.041)	(0.041)**	(0.042)**	(0.042)**
Male educ.	0.023	0.022	0.02	0.025	0.017	0.02	0.021
	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0056)**	(0.0057)**	(0.0057)**
GDP	0.095	0.07	0.047	0.1	0.058	0.035	0.053
	(0.031)**	(0.031)**	(0.03)	(0.031)**	(0.03)**	(0.03)	(0.03)*
Time trend	0.0066	0.0059	0.0052	0.0071	0.0065	0.0055	0.0064
	(0.00089)**	(0.00089)**	(0.00087)**	(0.00091)**	(0.00087)**	(0.00091)**	(0.00093)**
Observations	4979	4979	4979	4979	4979	4979	4868

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.0025

Table 14: Verbeek-Nijman (1993) Estimator, obs. 4877

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	-0.00077	-0.0039	-6e-04	-0.001	-0.053	0.0094	-0.13
	(0.00013)**	(0.0011)**	(0.00039)	(0.00016)**	(0.0058)**	(0.011)	(0.036)**
Impr. ws.	-0.039	-0.042	-0.046	-0.035	-0.07	-0.046	-0.049
	(0.021)*	(0.021)*	(0.021)**	(0.021)	(0.021)**	(0.022)**	(0.021)**
Impr. san.	0.13	0.12	0.13	0.14	0.091	0.13	0.12
	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**
Agr. empl.	-0.11	-0.087	-0.097	-0.12	-0.1	-0.1	-0.1
	(0.024)**	(0.025)**	(0.025)**	(0.024)**	(0.024)**	(0.025)**	(0.024)**
Agr. self-empl.	-0.14	-0.13	-0.13	-0.15	-0.13	-0.13	-0.13
	(0.017)**	(0.016)**	(0.016)**	(0.017)**	(0.016)**	(0.016)**	(0.016)**
Wealth	0.059	0.062	0.062	0.056	0.057	0.059	0.058
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**
Female educ.	0.015	0.016	0.015	0.013	0.017	0.015	0.016
	(0.0062)**	(0.0063)**	(0.0063)**	(0.0062)**	(0.0062)**	(0.0063)**	(0.0063)**
Urban	0.065	0.077	0.081	0.062	0.12	0.087	0.095
	(0.042)	(0.042)*	(0.042)*	(0.042)	(0.042)**	(0.042)**	(0.042)**
Male educ.	0.024	0.022	0.02	0.025	0.017	0.021	0.021
	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**	(0.0057)**
GDP	0.095	0.07	0.048	0.1	0.058	0.036	0.054
	(0.031)**	(0.031)**	(0.03)	(0.031)**	(0.03)**	(0.03)	(0.03)*
Time trend	0.0065	0.0059	0.0052	0.0071	0.0065	0.0054	0.0064
	(9e-04)**	(0.00089)**	(0.00087)**	(0.00091)**	(0.00087)**	(0.00091)**	(0.00093)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

Table 15: Verbeek-Nijman (1993) Estimator, obs. 4674

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	-0.00078	-0.0039	-0.0006	-0.001	-0.053	0.0087	-0.13
	(0.00013)**	(0.0011)**	(0.0004)	(0.00016)**	(0.0059)**	(0.011)	(0.036)**
Impr. ws.	-0.042	-0.045	-0.049	-0.038	-0.073	-0.049	-0.053
	(0.022)*	(0.022)**	(0.022)**	(0.022)*	(0.022)**	(0.022)**	(0.022)**
Impr. san.	0.13	0.12	0.13	0.14	0.093	0.13	0.13
	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**
Agr. empl.	-0.11	-0.088	-0.098	-0.12	-0.1	-0.11	-0.1
	(0.025)**	(0.025)**	(0.025)**	(0.025)**	(0.025)**	(0.025)**	(0.025)**
Agr. self-empl.	-0.14	-0.13	-0.13	-0.15	-0.13	-0.13	-0.13
	(0.017)**	(0.017)**	(0.017)**	(0.017)**	(0.016)**	(0.017)**	(0.017)**
Wealth	0.057	0.06	0.06	0.054	0.055	0.058	0.056
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**
Female educ.	0.013	0.014	0.014	0.012	0.016	0.013	0.014
	(0.0064)**	(0.0064)**	(0.0064)**	(0.0064)*	(0.0063)**	(0.0064)**	(0.0064)**
Urban	0.071	0.082	0.086	0.068	0.13	0.092	0.1
	(0.042)*	(0.042)*	(0.042)**	(0.042)	(0.042)**	(0.043)**	(0.042)**
Male educ.	0.026	0.024	0.022	0.028	0.019	0.023	0.023
	(0.0058)**	(0.0058)**	(0.0058)**	(0.0059)**	(0.0058)**	(0.0058)**	(0.0058)**
GDP	0.097	0.072	0.049	0.1	0.059	0.037	0.055
	(0.032)**	(0.031)**	(0.031)	(0.031)**	(0.03)**	(0.03)	(0.03)*
Time trend	0.0066	0.0059	0.0052	0.0072	0.0065	0.0055	0.0064
	(0.00091)**	(9e-04)**	(0.00088)**	(0.00092)**	(0.00088)**	(0.00092)**	(0.00094)**
Observations	4674	4674	4674	4674	4674	4674	4574

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.01

Table 16: Verbeek-Nijman (1993) Estimator, obs. 4060

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	-0.00079 (0.00014)**	-0.0039 (0.0012)**	-0.00057 (0.00041)	-0.0011 (0.00017)**	-0.053 (0.006)**	0.0072 (0.012)	-0.13 (0.037)**
Impr. ws.	-0.045 (0.022)**	-0.048 (0.023)**	-0.052 (0.023)**	-0.041 (0.022)*	-0.076 (0.022)**	-0.052 (0.023)**	-0.056 (0.023)**
Impr. san.	0.14 (0.022)**	0.13 (0.022)**	0.13 (0.022)**	0.14 (0.022)**	0.096 (0.022)**	0.14 (0.022)**	0.13 (0.022)**
Agr. empl.	-0.11 (0.026)**	-0.092 (0.026)**	-0.1 (0.026)**	-0.12 (0.026)**	-0.11 (0.025)**	-0.11 (0.026)**	-0.11 (0.026)**
Agr. self-empl.	-0.15 (0.017)**	-0.13 (0.017)**	-0.13 (0.017)**	-0.15 (0.017)**	-0.13 (0.017)**	-0.13 (0.017)**	-0.13 (0.017)**
Wealth	0.049 (0.017)**	0.052 (0.017)**	0.052 (0.017)**	0.046 (0.017)**	0.047 (0.017)**	0.05 (0.017)**	0.048 (0.017)**
Female educ.	0.014 (0.0067)**	0.015 (0.0067)**	0.015 (0.0067)**	0.013 (0.0067)*	0.017 (0.0067)**	0.015 (0.0067)**	0.015 (0.0067)**
Urban	0.067 (0.045)	0.078 (0.045)*	0.082 (0.045)*	0.064 (0.044)	0.13 (0.044)**	0.087 (0.045)*	0.096 (0.045)**
Male educ.	0.028 (0.0062)**	0.026 (0.0062)**	0.024 (0.0062)**	0.029 (0.0062)**	0.021 (0.0062)**	0.024 (0.0062)**	0.024 (0.0062)**
GDP	0.098 (0.032)**	0.072 (0.032)**	0.048 (0.032)	0.1 (0.032)**	0.059 (0.031)*	0.038 (0.031)	0.054 (0.031)*
Time trend	0.0067 (0.00094)**	0.006 (0.00093)**	0.0053 (0.00091)**	0.0073 (0.00095)**	0.0066 (0.00091)**	0.0055 (0.00095)**	0.0065 (0.00097)**
Observations	4060	4060	4060	4060	4060	4060	3982

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.025

Table 17: Verbeek-Nijman (1993) Estimator, obs. 2853

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	-0.00082	-0.004	-0.00059	-0.0011	-0.052	0.0054	-0.12
	(0.00015)**	(0.0013)**	(0.00045)	(0.00018)**	(0.0066)**	(0.013)	(0.041)**
Impr. ws.	-0.056	-0.06	-0.065	-0.052	-0.089	-0.065	-0.068
	(0.025)**	(0.025)**	(0.025)**	(0.025)**	(0.025)**	(0.025)**	(0.025)**
Impr. san.	0.14	0.13	0.14	0.15	0.1	0.14	0.13
	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**
Agr. empl.	-0.11	-0.086	-0.097	-0.12	-0.1	-0.1	-0.1
	(0.028)**	(0.029)**	(0.029)**	(0.028)**	(0.028)**	(0.029)**	(0.028)**
Agr. self-empl.	-0.15	-0.13	-0.13	-0.16	-0.13	-0.13	-0.14
	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**
Wealth	0.05	0.053	0.053	0.046	0.047	0.05	0.048
	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.02)**	(0.019)**
Female educ.	0.01	0.012	0.012	0.0085	0.014	0.011	0.012
	(0.0079)	(0.0079)	(0.008)	(0.0079)	(0.0079)*	(0.008)	(0.0079)
Urban	0.059	0.072	0.077	0.056	0.13	0.082	0.093
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)**	(0.052)	(0.051)*
Male educ.	0.033	0.03	0.028	0.035	0.024	0.029	0.029
	(0.0073)**	(0.0073)**	(0.0073)**	(0.0073)**	(0.0072)**	(0.0073)**	(0.0073)**
GDP	0.1	0.075	0.052	0.11	0.062	0.042	0.058
	(0.035)**	(0.035)**	(0.034)	(0.035)**	(0.034)*	(0.034)	(0.034)*
Time trend	0.0067	0.0059	0.0052	0.0073	0.0066	0.0054	0.0064
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.0011)**
Observations	2853	2853	2853	2853	2853	2853	2803

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.05

Table 18: Verbeek-Nijman (1993) Estimator, obs. 1497

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	-0.00082	-0.0039	-6e-04	-0.0011	-0.052	0.0053	-0.13
	(0.00018)**	(0.0015)**	(0.00053)	(0.00022)**	(0.0078)**	(0.015)	(0.049)**
Impr. ws.	-0.059	-0.064	-0.068	-0.055	-0.094	-0.068	-0.073
	(0.03)**	(0.03)**	(0.03)**	(0.03)*	(0.03)**	(0.03)**	(0.03)**
Impr. san.	0.15	0.14	0.14	0.15	0.11	0.15	0.14
	(0.028)**	(0.029)**	(0.029)**	(0.028)**	(0.029)**	(0.029)**	(0.029)**
Agr. empl.	-0.12	-0.1	-0.11	-0.13	-0.12	-0.12	-0.12
	(0.034)**	(0.035)**	(0.035)**	(0.035)**	(0.034)**	(0.035)**	(0.035)**
Agr. self-empl.	-0.16	-0.14	-0.14	-0.17	-0.14	-0.14	-0.15
	(0.024)**	(0.023)**	(0.023)**	(0.024)**	(0.023)**	(0.024)**	(0.023)**
Wealth	0.044	0.048	0.048	0.04	0.039	0.045	0.041
	(0.025)*	(0.025)*	(0.025)*	(0.025)	(0.025)	(0.026)*	(0.025)
Female educ.	0.014	0.016	0.017	0.011	0.02	0.016	0.017
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)*	(0.011)	(0.011)
Urban	0.058	0.072	0.078	0.055	0.14	0.084	0.097
	(0.064)	(0.065)	(0.065)	(0.064)	(0.064)**	(0.066)	(0.065)
Male educ.	0.031	0.028	0.025	0.034	0.02	0.026	0.026
	(0.0098)**	(0.0098)**	(0.0098)**	(0.0098)**	(0.0097)**	(0.0098)**	(0.0098)**
GDP	0.1	0.073	0.05	0.11	0.061	0.04	0.056
	(0.042)**	(0.042)*	(0.041)	(0.042)**	(0.04)	(0.041)	(0.041)
Time trend	0.0068	0.0061	0.0054	0.0075	0.0068	0.0056	0.0066
	(0.0012)**	(0.0012)**	(0.0012)**	(0.0013)**	(0.0012)**	(0.0013)**	(0.0013)**
Observations	1497	1497	1497	1497	1497	1497	1471

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.1

Table 19: Verbeek-Nijman (1993) Estimator, obs. 628

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	-0.00083	-0.0035	-0.00066	-0.0011	-0.051	0.007	-0.13
	(0.00024)**	(0.002)*	(0.00072)	(0.00029)**	(0.011)**	(0.021)	(0.066)*
Impr. ws.	-0.057	-0.062	-0.067	-0.052	-0.093	-0.067	-0.072
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)**	(0.041)	(0.041)*
Impr. san.	0.14	0.13	0.14	0.15	0.1	0.14	0.13
	(0.039)**	(0.039)**	(0.039)**	(0.039)**	(0.039)**	(0.039)**	(0.039)**
Agr. empl.	-0.13	-0.11	-0.12	-0.14	-0.13	-0.13	-0.13
	(0.047)**	(0.048)**	(0.048)**	(0.047)**	(0.047)**	(0.048)**	(0.047)**
Agr. self-empl.	-0.16	-0.14	-0.14	-0.17	-0.14	-0.14	-0.15
	(0.032)**	(0.032)**	(0.032)**	(0.032)**	(0.032)**	(0.032)**	(0.032)**
Wealth	0.033	0.037	0.037	0.029	0.026	0.033	0.029
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Female educ.	0.023	0.026	0.027	0.02	0.032	0.026	0.028
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)*	(0.017)	(0.017)*
Urban	0.059	0.078	0.085	0.055	0.15	0.095	0.11
	(0.092)	(0.093)	(0.093)	(0.092)	(0.092)*	(0.094)	(0.093)
Male educ.	0.026	0.022	0.018	0.03	0.011	0.019	0.019
	(0.014)*	(0.014)	(0.014)	(0.014)**	(0.014)	(0.014)	(0.014)
GDP	0.12	0.085	0.065	0.12	0.076	0.054	0.072
	(0.057)**	(0.057)	(0.055)	(0.057)**	(0.054)	(0.055)	(0.055)
Time trend	0.0067	0.0059	0.0053	0.0073	0.0068	0.0056	0.0066
	(0.0017)**	(0.0016)**	(0.0016)**	(0.0017)**	(0.0016)**	(0.0017)**	(0.0017)**
Observations	628	628	628	628	628	628	616

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.25

.3 Robustness: Estimation of joint specification of HP Filter and Trend ($\lambda = 6.25$)

Table 20: Verbeek-Nijman (1993) Estimator, HP Filter and Trend ($\lambda = 6.25$)

	Estimate	S.E.	t-value
HP filter	0.00043	0.00042	1
HP trend	-0.0012	0.00017	-6.9
Impr. ws.	-0.027	0.021	-1.3
Impr. san.	0.14	0.021	6.6
Agr. empl.	-0.13	0.024	-5.2
Agr. self-empl.	-0.15	0.017	-8.9
Wealth	0.06	0.015	3.9
Female educ.	0.012	0.0062	1.9
Urban	0.049	0.041	1.2
Male educ.	0.026	0.0057	4.6
GDP	0.12	0.031	3.8
Time trend	0.0072	9e-04	8

Dep. var.: WAZ, obs. 4877.

.4 Robustness: Re-defining Water Supply

Table 21: Verbeek-Nijman (1993) Estimator, altered WSS definition

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	-0.00085	-0.0042	-0.00062	-0.0011	-0.053	0.00082	-0.12
	(0.00015)**	(0.0013)**	(0.00045)	(0.00018)**	(0.0066)**	(0.013)	(0.041)**
Basic ws.	-0.056	-0.053	-0.055	-0.053	-0.092	-0.052	-0.055
	(0.026)**	(0.026)**	(0.027)**	(0.026)**	(0.027)**	(0.027)*	(0.027)**
Adv. ws.	-0.03	-0.028	-0.028	-0.03	-0.033	-0.028	-0.027
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Impr. san.	0.14	0.13	0.13	0.15	0.098	0.14	0.13
	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**
Agr. empl.	-0.11	-0.085	-0.096	-0.12	-0.1	-0.1	-0.1
	(0.028)**	(0.029)**	(0.029)**	(0.028)**	(0.028)**	(0.029)**	(0.028)**
Agr. self-empl.	-0.14	-0.13	-0.13	-0.15	-0.12	-0.13	-0.13
	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**
Wealth	0.042	0.045	0.045	0.039	0.032	0.044	0.04
	(0.021)**	(0.021)**	(0.021)**	(0.021)*	(0.021)	(0.021)**	(0.021)*
Female educ.	0.012	0.014	0.014	0.01	0.017	0.013	0.014
	(0.008)	(0.008)*	(0.008)*	(0.008)	(0.0079)**	(0.008)	(0.008)*
Urban	0.037	0.048	0.051	0.036	0.086	0.054	0.065
	(0.054)	(0.055)	(0.055)	(0.054)	(0.054)	(0.055)	(0.055)
Male educ.	0.032	0.03	0.027	0.035	0.023	0.028	0.028
	(0.0073)**	(0.0073)**	(0.0073)**	(0.0073)**	(0.0072)**	(0.0073)**	(0.0073)**
GDP	0.099	0.07	0.044	0.11	0.052	0.036	0.049
	(0.035)**	(0.035)**	(0.034)	(0.035)**	(0.033)	(0.034)	(0.034)
Time trend	0.0072	0.0064	0.0057	0.0078	0.0075	0.0057	0.0069
	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Weight-for-age z-score. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

.5 Robustness: Underweight

Table 22: Food prices and underweight ($WAZ < -2SD$)

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	0.00023	0.0016	3e-04	0.00029	0.0096	-0.0011	0.032
	(3.9e-05)**	(0.00032)**	(0.00011)**	(4.7e-05)**	(0.0017)**	(0.0033)	(0.01)**
Impr. ws.	0.0012	0.0018	0.0035	0.00034	0.0076	0.0033	0.0042
	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0063)	(0.0063)	(0.0063)
Impr. san.	-0.03	-0.026	-0.028	-0.032	-0.023	-0.03	-0.028
	(0.006)**	(0.006)**	(0.006)**	(0.006)**	(0.0061)**	(0.006)**	(0.006)**
Agr. empl.	0.019	0.011	0.015	0.022	0.018	0.018	0.018
	(0.0071)**	(0.0072)	(0.0072)**	(0.0071)**	(0.0071)**	(0.0071)**	(0.0071)**
Agr. self-empl.	0.028	0.023	0.023	0.029	0.023	0.023	0.024
	(0.0048)**	(0.0048)**	(0.0048)**	(0.0048)**	(0.0048)**	(0.0048)**	(0.0048)**
Wealth	-0.02	-0.021	-0.021	-0.019	-0.02	-0.02	-0.02
	(0.0045)**	(0.0045)**	(0.0046)**	(0.0045)**	(0.0045)**	(0.0046)**	(0.0046)**
Female educ.	-0.00024	-0.00066	-0.00062	8.8e-05	-0.00074	-3e-04	-0.00052
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Urban	-0.02	-0.023	-0.024	-0.019	-0.033	-0.026	-0.028
	(0.012)	(0.012)*	(0.012)**	(0.012)	(0.012)**	(0.012)**	(0.012)**
Male educ.	-0.0056	-0.0052	-0.0045	-0.006	-0.004	-0.0046	-0.0047
	(0.0017)**	(0.0017)**	(0.0017)**	(0.0017)**	(0.0017)**	(0.0017)**	(0.0017)**
GDP	-0.032	-0.028	-0.019	-0.032	-0.019	-0.015	-0.019
	(0.0091)**	(0.009)**	(0.0088)**	(0.0091)**	(0.0087)**	(0.0088)*	(0.0087)**
Time trend	-0.0025	-0.0024	-0.0021	-0.0027	-0.0023	-0.0021	-0.0024
	(0.00026)**	(0.00026)**	(0.00025)**	(0.00027)**	(0.00026)**	(0.00026)**	(0.00027)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Per cent of children underweight. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

.6 Robustness: Severe Underweight

Table 23: Food prices and severe underweight ($WAZ < -3SD$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	0.00014	0.0012	4e-04	0.00013	0.0074	-0.0034	0.027
	(2.6e-05)**	(0.00022)**	(7.8e-05)**	(3.2e-05)**	(0.0012)**	(0.0022)	(0.0072)**
Impr. ws.	0.0075	0.0077	0.0092	0.0074	0.012	0.009	0.0096
	(0.0043)*	(0.0043)*	(0.0043)**	(0.0043)*	(0.0043)**	(0.0043)**	(0.0043)**
Impr. san.	-0.011	-0.0084	-0.0089	-0.012	-0.0058	-0.012	-0.0098
	(0.0041)**	(0.0041)**	(0.0041)**	(0.0041)**	(0.0042)	(0.0041)**	(0.0041)**
Agr. empl.	0.017	0.011	0.012	0.018	0.016	0.017	0.016
	(0.0049)**	(0.0049)**	(0.0049)**	(0.0049)**	(0.0048)**	(0.0049)**	(0.0049)**
Agr. self-empl.	0.023	0.021	0.021	0.023	0.021	0.021	0.022
	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**	(0.0033)**
Wealth	-0.008	-0.0087	-0.0093	-0.0077	-0.0078	-0.0079	-0.0077
	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**	(0.0031)**
Female educ.	0.0012	0.00091	0.00075	0.0014	0.00084	0.0012	0.00099
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Urban	-0.023	-0.024	-0.025	-0.023	-0.032	-0.027	-0.028
	(0.0083)**	(0.0083)**	(0.0083)**	(0.0083)**	(0.0083)**	(0.0084)**	(0.0083)**
Male educ.	-0.003	-0.0029	-0.0022	-0.0031	-0.002	-0.0024	-0.0025
	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)*	(0.0011)**	(0.0011)**
GDP	-0.031	-0.03	-0.026	-0.029	-0.023	-0.02	-0.024
	(0.0062)**	(0.0062)**	(0.006)**	(0.0062)**	(0.0059)**	(0.006)**	(0.006)**
Time trend	-0.0016	-0.0016	-0.0013	-0.0016	-0.0016	-0.0015	-0.0016
	(0.00018)**	(0.00018)**	(0.00017)**	(0.00018)**	(0.00017)**	(0.00018)**	(0.00018)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Per cent of children severely underweight. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

.7 World Bank's Food Price Index in nominal USD

Table 24: Verbeek-Nijman (1993) Estimator, dep. var. WAZ, WB FPI in nominal USD.

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	-6e-04 (9.9e-05)**	-0.003 (0.00088)**	-0.00096 (0.00028)**	-0.00068 (0.00012)**	-0.061 (0.0057)**	0.097 (0.007)**	-0.19 (0.027)**
Impr. ws.	-0.036 (0.021)*	-0.041 (0.021)*	-0.049 (0.021)**	-0.033 (0.022)	-0.07 (0.021)**	-0.11 (0.022)**	-0.058 (0.021)**
Impr. san.	0.13 (0.021)**	0.12 (0.021)**	0.12 (0.021)**	0.13 (0.021)**	0.085 (0.021)**	0.13 (0.02)**	0.11 (0.021)**
Agr. empl.	-0.1 (0.024)**	-0.086 (0.025)**	-0.084 (0.025)**	-0.11 (0.024)**	-0.096 (0.024)**	-0.11 (0.024)**	-0.094 (0.024)**
Agr. self-empl.	-0.14 (0.016)**	-0.12 (0.016)**	-0.12 (0.016)**	-0.14 (0.017)**	-0.12 (0.016)**	-0.11 (0.016)**	-0.13 (0.016)**
Wealth	0.061 (0.016)**	0.062 (0.016)**	0.066 (0.016)**	0.057 (0.016)**	0.06 (0.015)**	0.053 (0.015)**	0.058 (0.016)**
Female educ.	0.015 (0.0062)**	0.016 (0.0063)**	0.017 (0.0063)**	0.013 (0.0063)**	0.017 (0.0062)**	0.012 (0.0061)*	0.018 (0.0063)**
urban	0.062 (0.042)	0.078 (0.042)*	0.083 (0.042)**	0.059 (0.042)	0.12 (0.041)**	0.16 (0.041)**	0.11 (0.042)**
Male educ.	0.024 (0.0057)**	0.022 (0.0057)**	0.019 (0.0057)**	0.025 (0.0058)**	0.018 (0.0056)**	0.018 (0.0056)**	0.02 (0.0057)**
GDP	0.098 (0.031)**	0.072 (0.031)**	0.061 (0.03)**	0.091 (0.031)**	0.065 (0.03)**	0.086 (0.029)**	0.083 (0.03)**
Time trend	0.0068 (9e-04)**	0.0059 (0.00089)**	0.0049 (0.00087)**	0.0072 (0.00093)**	0.0059 (0.00086)**	0.0065 (0.00086)**	0.0067 (0.00089)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Weight-for-age z-score. WB FPI in nominal USD. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

Table 25: Verbeek-Nijman (1993) Estimator, dep. var. underweight, WB FPI in nominal USD.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	0.00018 (2.9e-05)**	0.0011 (0.00026)**	0.00031 (8e-05)**	2e-04 (3.4e-05)**	0.011 (0.0017)**	-0.015 (0.0021)**	0.043 (0.008)**
Impr. ws.	0.00054 (0.0062)	0.0017 (0.0062)	0.0044 (0.0063)	-0.00054 (0.0063)	0.0078 (0.0063)	0.012 (0.0064)**	0.0061 (0.0063)
Impr. san.	-0.029 (0.006)**	-0.026 (0.0061)**	-0.026 (0.0061)**	-0.031 (0.006)**	-0.022 (0.0061)**	-0.03 (0.006)**	-0.027 (0.006)**
Agr. empl.	0.018 (0.0071)**	0.012 (0.0072)	0.012 (0.0073)	0.021 (0.0071)**	0.017 (0.0071)**	0.02 (0.0071)**	0.016 (0.0071)**
Agr. self-empl.	0.027 (0.0048)**	0.022 (0.0048)**	0.022 (0.0048)**	0.028 (0.0048)**	0.022 (0.0048)**	0.022 (0.0048)**	0.023 (0.0048)**
Wealth	-0.021 (0.0045)**	-0.021 (0.0045)**	-0.022 (0.0046)**	-0.02 (0.0045)**	-0.021 (0.0045)**	-0.019 (0.0045)**	-0.02 (0.0045)**
Female educ.	-3e-04 (0.0018)	-0.00059 (0.0018)	-0.00092 (0.0018)	1e-04 (0.0018)	-0.00071 (0.0018)	0.00018 (0.0018)	-0.00095 (0.0018)
urban	-0.019 (0.012)	-0.023 (0.012)*	-0.025 (0.012)**	-0.018 (0.012)	-0.032 (0.012)**	-0.037 (0.012)**	-0.03 (0.012)**
Male educ.	-0.0056 (0.0017)**	-0.0052 (0.0017)**	-0.0042 (0.0017)**	-0.006 (0.0017)**	-0.0042 (0.0017)**	-0.0043 (0.0017)**	-0.0045 (0.0017)**
GDP	-0.033 (0.0091)**	-0.027 (0.0091)**	-0.022 (0.0088)**	-0.031 (0.009)**	-0.02 (0.0087)**	-0.022 (0.0087)**	-0.025 (0.0088)**
Time trend	-0.0026 (0.00026)**	-0.0024 (0.00026)**	-0.002 (0.00025)**	-0.0027 (0.00027)**	-0.0022 (0.00025)**	-0.0023 (0.00025)**	-0.0025 (0.00026)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Underweight. WB FPI in nominal USD. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

.8 World Bank's Food Price Index in real USD

Table 26: Verbeek-Nijman (1993) Estimator, dep. var. WAZ, WB FPI in real USD.

	(1) FPI	(2) CoV	(3) HP Filter	(4) HP Trend	(5) Price Hike	(6) Price Drop	(7) PChange
Price Index	-0.0011	-0.003	-0.0027	-0.0011	-0.062	0.095	-0.17
	(0.00016)**	(0.00088)**	(4e-04)**	(2e-04)**	(0.0059)**	(0.0071)**	(0.037)**
Impr. ws.	-0.035	-0.041	-0.055	-0.032	-0.072	-0.11	-0.049
	(0.021)	(0.021)*	(0.021)**	(0.022)	(0.021)**	(0.022)**	(0.021)**
Impr. san.	0.13	0.12	0.11	0.13	0.082	0.13	0.12
	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.02)**	(0.021)**
Agr. empl.	-0.097	-0.086	-0.062	-0.11	-0.098	-0.11	-0.093
	(0.024)**	(0.025)**	(0.025)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**
Agr. self-empl.	-0.14	-0.12	-0.11	-0.14	-0.12	-0.11	-0.12
	(0.016)**	(0.016)**	(0.016)**	(0.017)**	(0.016)**	(0.016)**	(0.016)**
Wealth	0.062	0.062	0.071	0.057	0.059	0.048	0.061
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.015)**	(0.015)**	(0.016)**
Female educ.	0.014	0.016	0.017	0.013	0.017	0.012	0.017
	(0.0062)**	(0.0063)**	(0.0063)**	(0.0063)**	(0.0062)**	(0.0062)**	(0.0063)**
urban	0.056	0.078	0.081	0.057	0.13	0.17	0.08
	(0.042)	(0.042)*	(0.042)**	(0.042)	(0.041)**	(0.042)**	(0.042)*
Male educ.	0.025	0.022	0.019	0.026	0.017	0.018	0.021
	(0.0057)**	(0.0057)**	(0.0057)**	(0.0058)**	(0.0057)**	(0.0056)**	(0.0057)**
GDP	0.11	0.072	0.084	0.089	0.048	0.074	0.068
	(0.031)**	(0.031)**	(0.03)**	(0.031)**	(0.03)	(0.029)**	(0.03)**
Time trend	0.0075	0.0059	0.0046	0.0077	0.0069	0.0073	0.0059
	(0.00092)**	(0.00089)**	(0.00087)**	(0.00097)**	(0.00088)**	(0.00087)**	(0.00088)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Weight-for-age z-score. WB FPI in real USD. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

Table 27: Verbeek-Nijman (1993) Estimator, dep. var. underweight, WB FPI in real USD.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FPI	CoV	HP Filter	HP Trend	Price Hike	Price Drop	PChange
Price Index	0.00032 (4.6e-05)**	0.0011 (0.00026)**	0.00067 (0.00012)**	0.00033 (5.8e-05)**	0.012 (0.0017)**	-0.016 (0.0021)**	0.054 (0.011)**
Impr. ws.	4e-04 (0.0062)	0.0017 (0.0062)	0.0055 (0.0062)	-0.00088 (0.0063)	0.0082 (0.0063)	0.014 (0.0064)**	0.0044 (0.0062)
Impr. san.	-0.029 (0.006)**	-0.026 (0.0061)**	-0.026 (0.006)**	-0.031 (0.006)**	-0.021 (0.0061)**	-0.03 (0.006)**	-0.028 (0.006)**
Agr. empl.	0.016 (0.0071)**	0.012 (0.0072)	0.0079 (0.0073)	0.021 (0.0071)**	0.017 (0.0071)**	0.02 (0.0071)**	0.015 (0.0071)**
Agr. self-empl.	0.026 (0.0048)**	0.022 (0.0048)**	0.02 (0.0048)**	0.028 (0.0048)**	0.023 (0.0048)**	0.021 (0.0048)**	0.023 (0.0048)**
Wealth	-0.021 (0.0045)**	-0.021 (0.0045)**	-0.023 (0.0046)**	-0.02 (0.0045)**	-0.02 (0.0045)**	-0.018 (0.0045)**	-0.021 (0.0045)**
Female educ.	-0.00022 (0.0018)	-0.00059 (0.0018)	-0.00096 (0.0018)	0.00011 (0.0018)	-0.00073 (0.0018)	8.3e-05 (0.0018)	-0.001 (0.0018)
urban	-0.018 (0.012)	-0.023 (0.012)*	-0.025 (0.012)**	-0.017 (0.012)	-0.033 (0.012)**	-0.04 (0.012)**	-0.024 (0.012)**
Male educ.	-0.0058 (0.0017)**	-0.0052 (0.0017)**	-0.0043 (0.0017)**	-0.0061 (0.0017)**	-0.004 (0.0017)**	-0.0041 (0.0017)**	-0.0046 (0.0017)**
GDP	-0.034 (0.0091)**	-0.027 (0.0091)**	-0.026 (0.0089)**	-0.03 (0.009)**	-0.017 (0.0086)*	-0.021 (0.0087)**	-0.024 (0.0088)**
Time trend	-0.0027 (0.00027)**	-0.0024 (0.00026)**	-0.002 (0.00025)**	-0.0029 (0.00028)**	-0.0024 (0.00026)**	-0.0025 (0.00026)**	-0.0023 (0.00026)**
Observations	4877	4877	4877	4877	4877	4877	4770

Dependent variable: Underweight. WB FPI in real USD. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$

Verbeek-Nijman (1993) estimator, min. density per cohort: 0.005

.9 Descriptive statistics on child underweight by country

Table 28: Weighted descriptive statistics on underweight (pooled cross section)

Country	Year	Min.	1st Qu.	Median	Mean	s.d.	3rd Qu.	Max.
India	2006	0	0	1	0.55	0.5	1	1
Bangladesh	2011	0	0	1	0.5	0.5	1	1
Niger	2006	0	0	0	0.49	0.5	1	1
Madagascar	2004	0	0	0	0.48	0.5	1	1
Mozambique	2004	0	0	0	0.44	0.51	1	1
Chad	2004	0	0	0	0.4	0.49	1	1
Ethiopia	2003	0	0	0	0.39	0.49	1	1
Mali	2006	0	0	0	0.37	0.48	1	1
Cambodia	2011	0	0	0	0.36	0.49	1	1
Burkina Faso	2010	0	0	0	0.36	0.48	1	1
Guatemala	1999	0	0	0	0.31	0.46	1	1
Guinea	2005	0	0	0	0.31	0.46	1	1
Nigeria	2008	0	0	0	0.3	0.46	1	1
Kenya	2009	0	0	0	0.28	0.45	1	1
Namibia	2007	0	0	0	0.28	0.45	1	1
Senegal	2011	0	0	0	0.28	0.45	1	1
Benin	2006	0	0	0	0.27	0.44	1	1
Tanzania	2010	0	0	0	0.27	0.44	1	1
Zambia	2007	0	0	0	0.23	0.42	0	1
Ghana	2008	0	0	0	0.22	0.42	0	1
Lesotho	2010	0	0	0	0.22	0.42	0	1
Malawi	2010	0	0	0	0.22	0.41	0	1
Uganda	2011	0	0	0	0.22	0.41	0	1
Cameroon	2011	0	0	0	0.21	0.41	0	1
Haiti	2006	0	0	0	0.21	0.41	0	1
Zimbabwe	2011	0	0	0	0.18	0.38	0	1
Rwanda	2011	0	0	0	0.17	0.38	0	1
Morocco	2004	0	0	0	0.16	0.36	0	1
Nicaragua	2001	0	0	0	0.12	0.33	0	1
Egypt	2008	0	0	0	0.1	0.3	0	1
Peru	2008	0	0	0	0.088	0.28	0	1
Bolivia	2008	0	0	0	0.087	0.28	0	1
Colombia	2010	0	0	0	0.076	0.27	0	1
Dominican Republic	2007	0	0	0	0.072	0.26	0	1
Kazakhstan	1999	0	0	0	0.071	0.26	0	1
Jordan	2007	0	0	0	0.068	0.25	0	1
Armenia	2010	0	0	0	0.066	0.25	0	1
Turkey	2004	0	0	0	0.06	0.24	0	1

Table 29: Weighted descriptive statistics on severe underweight (pooled cross section)

Country	Year	Min.	1st Qu.	Median	Mean	s.d.	3rd Qu.	Max.
India	2006	0	0	0	0.26	0.44	1	1
Niger	2006	0	0	0	0.22	0.41	0	1
Bangladesh	2011	0	0	0	0.2	0.4	0	1
Madagascar	2004	0	0	0	0.2	0.4	0	1
Mozambique	2004	0	0	0	0.19	0.4	0	1
Chad	2004	0	0	0	0.17	0.38	0	1
Cambodia	2011	0	0	0	0.15	0.37	0	1
Ethiopia	2003	0	0	0	0.15	0.36	0	1
Mali	2006	0	0	0	0.15	0.36	0	1
Burkina Faso	2010	0	0	0	0.14	0.35	0	1
Nigeria	2008	0	0	0	0.13	0.34	0	1
Guinea	2005	0	0	0	0.12	0.33	0	1
Lesotho	2010	0	0	0	0.1	0.3	0	1
Senegal	2011	0	0	0	0.098	0.3	0	1
Guatemala	1999	0	0	0	0.093	0.29	0	1
Benin	2006	0	0	0	0.088	0.28	0	1
Kenya	2009	0	0	0	0.087	0.28	0	1
Cameroon	2011	0	0	0	0.08	0.27	0	1
Tanzania	2010	0	0	0	0.08	0.27	0	1
Haiti	2006	0	0	0	0.076	0.27	0	1
Namibia	2007	0	0	0	0.074	0.26	0	1
Ghana	2008	0	0	0	0.068	0.25	0	1
Zambia	2007	0	0	0	0.066	0.25	0	1
Uganda	2011	0	0	0	0.064	0.24	0	1
Malawi	2010	0	0	0	0.054	0.23	0	1
Morocco	2004	0	0	0	0.054	0.23	0	1
Rwanda	2011	0	0	0	0.038	0.19	0	1
Zimbabwe	2011	0	0	0	0.036	0.19	0	1
Nicaragua	2001	0	0	0	0.032	0.18	0	1
Egypt	2008	0	0	0	0.026	0.16	0	1
Armenia	2010	0	0	0	0.019	0.14	0	1
Bolivia	2008	0	0	0	0.019	0.14	0	1
Jordan	2007	0	0	0	0.016	0.12	0	1
Peru	2008	0	0	0	0.015	0.12	0	1
Dominican Republic	2007	0	0	0	0.014	0.12	0	1
Turkey	2004	0	0	0	0.014	0.12	0	1
Kazakhstan	1999	0	0	0	0.013	0.11	0	1
Colombia	2010	0	0	0	0.012	0.11	0	1