INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

IFPRI Discussion Paper 01882

November 2019

Agriculture-Nutrition Linkages, Cooking Time, Intrahousehold Equality among Women and Children

Evidence from Tajikistan

Hiroyuki Takeshima

Kamiljon Akramov

Allen Park

Jarilkasin Ilyasov

Tanzila Ergasheva

Development Strategy and Governance Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

AUTHORS

Hiroyuki Takeshima (H.takeshima@cgiar.org) is a Senior Research Fellow in the Development Strategy and Governance Division of the International Food Policy Research Institute (IFPRI), Washington, DC.

Kamiljon Akramov (K.akramov@cgiar.org) is a Senior Research Fellow in the Development Strategy and Governance Division at IFPRI, Washington, DC.

Allen Park (A.park@cgiar.org) is a Senior Research Analyst in the Development Strategy and Governance Division at IFPRI, Washington, DC.

Jarilkasin Ilyasov (J.Ilyasov@cgiar.org) is a Senior Research Analyst in the Development Strategy and Governance Division at IFPRI, Washington, DC.

Tanzila Ergasheva (tanzila.e@gmail.com) is a Senior Researcher at the Institute of Agricultural Economics, Tajik Academy of Agricultural Sciences, Dushanbe, Tajikistan.

Notices

Agriculture-nutrition linkages, cooking time, intrahousehold equality among women and children: Evidence from Tajikistan

Hiroyuki Takeshima, International Food Policy Research Institute (IFPRI)
Kamiljon Akramov, IFPRI
Allen Park, IFPRI
Jarilkasin Ilyasov, IFPRI
Tanzila Ergasheva, Tajik Academy of Agricultural Sciences (TAAS)

Abstract: Household-level agriculture-nutrition linkage (ANL) tends to be strong in a rural subsistence setting with limited access to the food market. In such a context, markets for food processing services also may be imperfect, and consequently a household's time-investments in cooking may become important. Using the primary data in Tajikistan, we show that longer periods of time dedicated to cooking by women in the household often significantly enhance household-level ANL. Furthermore, an increase in the diversity, scale, and efficiency of household production, as well as longer cooking time, can also reduce intrahousehold inequality in nutritional outcomes among women and children. These effects are stronger in areas with lower nighttime light intensity and for households with lower values of cooking assets. In a context where household-level ANL is strong, ANL may also depend on households' self-production of complementary inputs, including cooking services. This dependence reveals both unique opportunities for and vulnerabilities of ANL for the rural poor.

Keywords: agriculture-nutrition linkage, cooking time, intrahousehold equality, inverse-probability weighting, generalized propensity score, Tajikistan

Acknowledgments

We thank the participants of the Annual Eurasian Food Security Conference in Dushanbe, 2017, the Third and the Fourth Annual International Conference on Agriculture, Food Security, and Nutrition in Eurasia in Moscow, 2018 and 2019, and the seminar participants at the Tajik Academy of Agricultural Sciences (TAAS) in September 2018 for providing useful feedbacks for the earlier version of the paper; and we thank the field staff from Zerkalo for the 2015 and 2018 data collection. We also thank the United States Agency for International Development (USAID), the CGIAR Research Program on Policies, Institutions, and Markets (PIM), and the CGIAR Research Program on Agriculture for Nutrition and Health (A4NH), which are led by the International Food Policy Research Institute (IFPRI), as well as the government of Japan through its support to IFPRI, for providing financial support to conduct this study. Any opinions expressed here belong to the authors and do not reflect those of its collaborators. The authors are responsible for all remaining errors.

1 Introduction

Strengthening agriculture-nutrition linkage (ANL) has been considered important for improving nutrition security, especially in areas with less market access where local- and household-level production of food is a significant source of food consumed (Fan et al. 2019). Growing evidence around the world shows substantial evidence for such linkages (for example, Jones 2017; Ruel et al. 2018). Strengthening ANL is part of a "food-based" approach which is sometimes more advantageous than medical approaches, in terms of sustainability (Howson et al. 1998; Weinberger & Swai 2006) and resilience against the breakdown of infrastructure for supplementation and fortification (Allen & Gillespie 2001).

The context in which household-level ANL tends to be important is often characterized by greater market failures, such as the failure of food markets due to remoteness and other constraints (for example, Hirvonen & Hoddinott 2017). In such a context, the effectiveness of ANL also may be more affected by certain market-failures. These are related to cooking time, intrahousehold inequality among women or children, and technical efficiency in agriculture across locations. For a food-based approach, cooking processes that affect the bioavailability of nutrients can be important inputs for nutrition production. With more severe market failures, self-production of cooking services at the household level becomes important, unlike in areas with access to food markets, where economies of scale in cooking are more utilized (more food items have already been pre-cooked by more specialized agents), and cooking services also can more easily be purchased rather than provided by the household in a subsistence way. In areas with good food-market access, intrahousehold inequality in nutrition (conditional on household and individual characteristics) may be mostly due to consumer-side constraints. However, in areas with food-market failures, inequality may also arise from supply-side factors (household-level production), and thus potentially be magnified. Finally, in areas that are less integrated spatially, locational variations in technical efficiency matter for ANL. The direct evidence on how these factors affect the effectiveness of ANL is, however, still scarce in the literature.

This paper attempts to fill this knowledge gap using the data from Tajikistan. Specifically, using household- and individual-level primary data, we provide evidence on how cooking-time inputs affect the impact of household-level agricultural production practices (APP) and the technical efficiency of local agricultural production on the nutritional outcomes of women and children, as well as intrahousehold inequality in certain nutritional outcomes among women and / or children. We employ instrumental-variable generalized method of moments (IVGMM) and an extension of the nested propensity-score method (Huber 2014) to the generalized-propensity-score-based inverse probability weighting method (GPS-IPW) (Imbens 2000; Bodnar et al. 2004; Flores & Mitnik 2013) (nested GPS-IPW, or NGPS-IPW hereafter), to address the potentially complex form of endogeneity of APP and cooking time with respect to nutritional outcomes.

Tajikistan is a suitable case to investigate the issue of ANL. It is the poorest country in the Central Asia region, which has generally been understudied in the development literature. Furthermore, through the legacy of the Soviet era, the country has a relatively good education system and has also spent a relatively high share of its gross domestic product (GDP) on the health sector (7 percent in 2017 as compared to 5.5 percent for low- and middle-income countries) (World Bank 2019).[1] Yet malnutrition remains widespread in Tajikistan, suggesting

[1] In Tajikistan, the adult literacy rate has been more than 98 percent since the late 1980s (World Bank 2019), and the adult population 25 years old or above has had more than 10 years of formal education since 1990, much higher than developing Asia (Barro & Lee 2013).

potentially important roles for the agricultural sector in addressing malnutrition that are not covered by other sectors.

This study contributes to various strands of literature. First, it builds on the general literature on ANL (for example, World Bank 2007; Ruel et al. 2018; Fan et al. 2019), including studies focusing on crop diversification (Shively et al. 2015; Hirvonen and Hoddinott 2017) and production scale (Kumar et al. 2015), by offering deeper insights into the heterogeneity of ANL's effectiveness, factors contributing to such heterogeneity (cooking time in particular), and the nature of heterogeneity (intrahousehold equality). Second, it builds on the literature on time-use and nutrition (Komatsu et al. 2018; Johnston et al. 2018) by providing a more concrete example of the context in which cooking time affects nutritional outcomes. It also distantly relates to the broader literature on time-allocation decisions (for example, Becker 1965) by providing richer insights into the returns to cooking time. Third, the study builds on a large literature on intrahousehold variations on nutrition (for example, Pitt et al. 1990; Haddad et al. 1997), and variations among children (for example, Finaret et al. 2018) and women in particular (for example, Bhandari et al. 2016; Harris-Fry et al. 2017, 2018). Fourth, the study also contributes to the related literature on Tajikistan (Azzarri & Zezza 2011; Mukhamedova & Wegerich 2018; Wood et al. 2018; Klassen et al. 2018; Takeshima et al. 2019). Last, the study also builds methodologically on the literature on impact evaluation, particularly nested propensity-score methods (Huber 2014), GPS-IPW (Bodnar et al. 2004; Flores & Mitnik 2013), as well as the literature on technical efficiency and methodologies like data envelopment analyses (DEA) (for example, Charnes et al. 1994).

The rest of the paper is structured in the following way. Section 2 discusses the theoretical framework. Section 3 describes the empirical methods. Section 4 describes data and descriptive statistics. Section 5 presents the results, while section 6 concludes.

2 Theoretical framework

2.1 Role of household cooking time on ANL

The demand for nutritional outcomes of individual i (N_i) in household h is selected by maximizing utility,

$$U = U(N_i; Z_{h,i}) \tag{1}$$

which depends on the inherent preference that depends on individual and household characteristics $Z_{h,i}$. Here, for simplicity, we drop the subscript h and i (we will reinstate them later when discussing intrahousehold equality).

N is supplied by available food F (either home-produced A, or purchased F_P), household members' cooking time T, and functions of cooking technologies C, level of food market access M, and again Z (which can affect non-food sources of nutrition).

$$N = f(F, T; C, M, Z) \tag{2}$$

Note T does not include cooking provided by non-household members, such as purchased cooking services. The equilibrium nutritional outcome N^* is jointly determined by these demand and supply factors.[2]

[2]It is beyond the scope of this study to separate the effects of ANL and cooking time into supply and demand for nutrition. We focus on equilibrium nutritional outcomes, and we interpret their improvements as positive, although strictly speaking, some of the seeming "improvement" may be due to the increased nutrition requirements as a result of greater engagements in agricultural production or cooking (for members who are reporting cooking time). More precise interpretations must be addressed in future studies.

In low-income countries with food poverty (so that nutrition is still constrained by food availability F), we are likely to have

$$\frac{\partial N^*}{\partial F} > 0. \tag{3}$$

The ANL literature generally suggests that, in rural areas with low M, we tend to have

$$\frac{\partial F}{\partial A} > 0 \tag{4}$$

because of relatively higher costs for acquiring F_P given Z.

Because low M would indicate relative scarcity of pre-cooked food, or most food items must be cooked before becoming digestible, or retaining bioavailability of nutrients in food items may require more careful cooking, $\frac{\partial N^*}{\partial F}$ responds more positively to cooking inputs. Furthermore, because low M is also associated with high cooking-service costs, cooking inputs are supplied mostly by households' own cooking inputs, T. Thus,

$$\frac{\partial^2 N^*}{\partial F \partial T} > 0.^3 \tag{5}$$

It is also likely that cooking-time T and cooking technologies are substitutes, so that $\frac{\partial^2 N^*}{\partial T \partial C} < 0$.[4] Therefore, combined with (5), we are likely to have

$$\frac{\partial \left(\frac{\partial^2 N^*}{\partial F \partial T} \right)}{\partial C} < 0 \tag{6}$$

Because we have $\frac{\partial F}{\partial A} > 0$, condition (6) suggests

$$\frac{\partial \left(\frac{\partial^2 N^*}{\partial A \partial T} \right)}{\partial C} < 0 \tag{7}$$

Household cooking time T may also be substituted with M, because as M rises, the access to either pre-cooked food or affordable cooking services may improve. Similarly, higher M may be associated with more urban income-earning opportunities which can provide alternative means to improve nutrition (for example, Blau et al. 1996 in the Philippines, Bamji & Thimayamma 2000 in South India), and thus higher M raises the opportunity cost of T for most individuals. Therefore, $\frac{\partial^2 N^*}{\partial T \partial M} < 0$. Using the same argument as cooking technologies, we then have

$$\frac{\partial \left(\frac{\partial^2 N^*}{\partial A \partial T} \right)}{\partial M} < 0. \tag{8}$$

Conditions (7) and (8) lead to hypothesis 1:

<u>*Hypothesis 1: Conditional on household characteristics Z, household agricultural production (greater diversity or production scale) and cooking time is generally complementary in*</u>

---

[3]Note that this is not simply because more cooking activity raises the nutritional requirements of the person engaged in cooking, because N here refers to all household members.

[4]Higher cooking technologies raise marginal returns to a unit of cooking time. They may induce greater cooking time if cooking is undertaken for commercial and income-earning purposes, because the demand curve is that of the market and is fairly flat. However, cooking for household members faces a declining demand curve, and thus higher cooking technologies become substitutes for cooking time.

improving equilibrium nutritional outcomes of women and children, and this effect is stronger for households with lower cooking technologies or in rural areas.

The hypothesis 1 may not hold if some of the aforementioned conditions fail. Therefore, whether hypothesis 1 holds or not is an important empirical question.

2.2 Intrahousehold inequality

Equilibrium nutritional outcomes of each household member maximizes a certain utility function. Based on the realization of N_i^*, some indicators of intrahousehold equality σ^* are obtained:

$$N_i^* = \arg\max_{N_i} U(N_i; Z_{h,i})$$
$$\sigma_h^* = \sigma\left(N_i^*; Z_{h,i}\right). \tag{9}$$

Note σ_h^* is conditional on Z (and its intrahousehold variation) because observable Z is assumed to explain most of the variations in intrahousehold allocations (including activity-level, pregnancy status, etc.).

It is beyond the scope of this study to assess how the utility function is maximized. For the sake of presenting a theoretical framework, we consider the case in which allocation is made by a decisionmaker in the household, with the goal of maximizing the aggregate consumer surplus (or utility) of all members while meeting the resource constraint. In this particular case, N_i^* is determined such that

$$\left.\frac{\partial U(N_i; Z)}{\partial N_i}\right|_{N_i=\widehat{N}_i} = \left.\frac{\partial U\left(N_j; Z\right)}{\partial N_j}\right|_{N_j=\widehat{N}_j} \quad \forall j \neq i \tag{10}$$

so that every member's marginal utility from an additional unit of nutrition is equated. When this holds, and if the utility function is the same across members conditional on Z (so that all variations in inherent preference are solely explained by observable characteristics), we should have $\sigma_h^* = \sigma(N_i^*; Z) = 0$, meaning perfect intrahousehold equality.

Even in such a case, N_i^* may deviate from $\widehat{N}_i$ if transaction costs in achieving the aforementioned allocations are greater than the returns from reallocations. These transaction costs will thus affect σ_h^*, conditional on Z.

A and T may jointly reduce σ_h^* if they affect such transactions costs in such ways. For example, the greater overall availability of food and longer cooking time may reduce such transactions costs. However, they can also operate in opposite ways.[5] The discussion here is made for illustrative purposes, and how A and T affect σ_h^* conditional on Z is therefore an empirical question which we aim to investigate.

Hypothesis 2: Household agricultural production (greater diversity or production scale) and cooking time are generally complementary in reducing intrahousehold nutritional outcomes

[5] An extreme example is as follows. If there is only one apple for two household members, the apple needs to be cut, incurring certain transaction costs. If there are two apples, each can simply be given to each person, without any transaction costs. If, however, there is additional apple (and thus a total of three apples), this additional apple is likely to have to be cut into half and shared by these two people, to equate their marginal utility. In this case, a greater quantity of food (apple) ends up increasing transactions costs for equating an individual's marginal utility. If the transactions costs are too high and they give up sharing the third apple, two and one apples are consumed by each person, respectively, leading to inequality in consumption.

among women and children, and this effect is stronger for households with lower cooking technologies or in rural areas.

2.3 Technical efficiency

The theoretical framework on the effects of technical efficiency in agriculture is similar to hypothesis 1. With higher efficiency, either greater A or greater resources allocated for other purposes can improve nutritional outcomes. On the one hand, if greater A is achieved, and if cooking time T is complementary, then higher technical efficiency and T can be complementary to improving nutrition. On the other hand, the opportunity costs of resources used to raise technical efficiency in the area may be high (for example, they can be used for other means to more directly raise nutrition) to produce the same amount of food, or higher technical efficiency may not lead to sufficient food availability if households simply reduce inputs use. In such a case, raising technical efficiency may not improve nutritional outcomes.

Hypothesis 3: Higher technical efficiency in agriculture and cooking time are complementary to each other in improving nutritional outcomes, and this effect is stronger for households with lower cooking technologies or in rural areas; these conditions may largely hold in the current setting of the studied area in Tajikistan.

As was mentioned above, this paper addresses research questions that are somewhat independent of each other, driven by data availability. Nonetheless, evidence of each of these questions is an important piece that helps us better understand the overall agricultural-nutrition linkages (Figure 1). Figure 1 illustrates the overarching framework presented in Fan et al. (2019). The research question on cooking time relates to the particular linkages between *food access* and *diet*, among others; the research question on intrahousehold equality among women corresponds to the linkages between *food production* and *individual nutrition outcomes*; while the research question on technical efficiency corresponds to *food production* and *income* linkages.

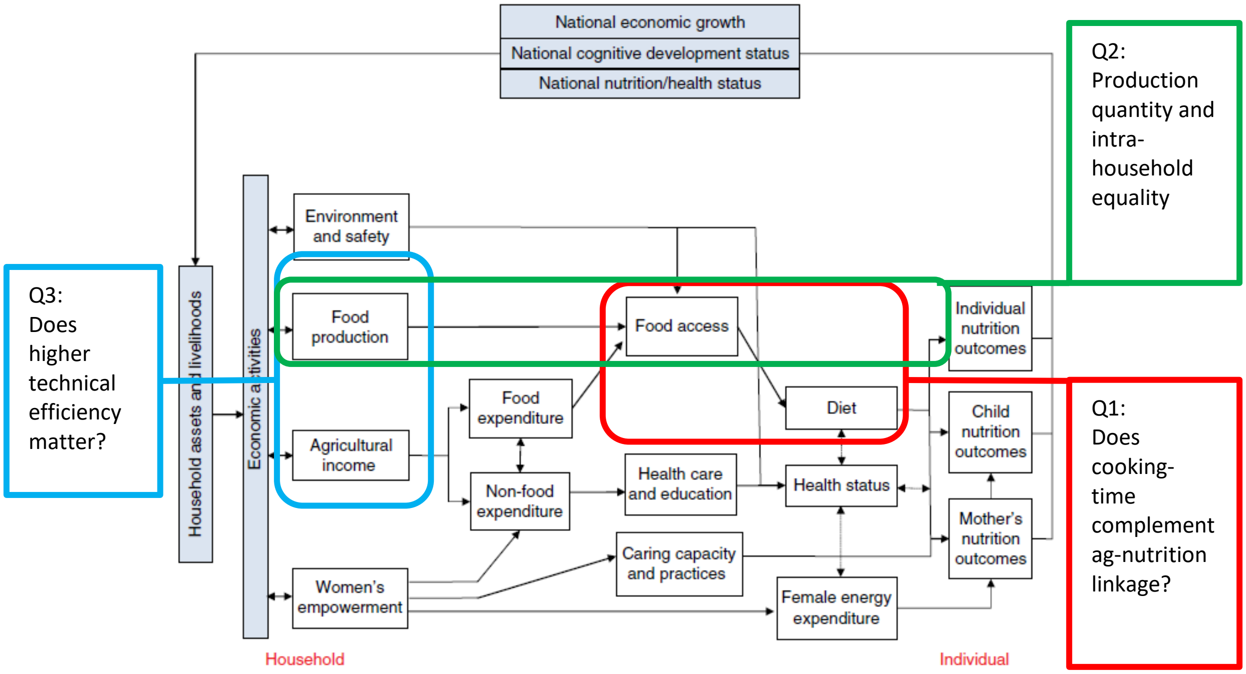

Figure 1. Relevance of research questions to the overall framework of agriculture-nutrition linkage

Source: Authors' modifications based on Fan et al. (2019).

3 Empirical models

In our empirical approaches, we essentially regress various nutritional outcomes of interest (as well as their intrahousehold variations among children or among female-household members), on key household-level APP and technical efficiency, as well as cooking time. Nutritional outcomes of interest include women's dietary diversity score (WDS) among women of reproductive age (WRA) and whether WDS met the minimum acceptable dietary diversity score (WDSM) of 5 (FAO & FIH 360, 2016); and children's minimum acceptable diet (CMAD), children's minimum acceptable dietary diversity (CMDD) (WHO 2010), children's weight-for-age Z-score (WAZ), and weight-for-height Z-score (WHZ). These indicators are often used in the literature to capture key aspects of nutritional outcomes (Ruel et al. 2018). APP consists of the diversity of food groups produced (agricultural diversity score [ADS]) and the production scale proxied by agricultural production values (APV), which have been commonly used in the aforementioned ANL literature. Results are compared across different levels of cooking technologies (proxied by the value of cooking equipment [VCE]) and the level of market access (proxied by nighttime light density that is closely associated with the level of urbanization).

The main concern in our empirical model is the potential endogeneity of APP and cooking time with respect to nutritional outcomes. We employ NGPS-IPW, as well as standard IVGMM, to mitigate such endogeneity issues.

Each approach has its advantages and shortcomings. IVGMM is straightforward to estimate. However, selection of instrumental variables (IVs) can always be difficult, even when they pass specifications tests—this is because, while those tests provide a necessary condition that the IV is suitable, whether they provide sufficient conditions of IV suitability requires the assumption that the main structural equation is also correctly specified. Furthermore, reliability of IV estimation depends on having sufficiently many IVs relative to the number of endogenous variables, which often poses practical challenges (Davidson & McKinnon 1993; Deaton 1995). Under reasonable assumptions, NGPS-IPW offers a practical alternative when exclusion restrictions are unclear. However, as in any propensity-score based method, it relies on the famous assumptions of selection-on-observable (Hirano & Imbens 2004; Huber 2014), that is, regressors of interest (APP and cooking time in our case) are no longer endogenous to nutritional outcome conditional on propensity scores estimated from the observable characteristics. Estimating both IVGMM and NGPS-IPW can thus improve the robustness of our results against the possible violations of relevant assumptions.

3.1 Overall empirical framework

For all three research questions, our empirical models largely take the following forms:

$$y = f(F_A \cdot T \cdot C \cdot M; Z) \tag{11}$$

where y denote the set of dependent variables (individual nutritional outcome N_i or household-level inequality in nutritional outcomes σ_h^*). The notations " $\cdot$ " indicate the interactions between each factor. In other words, we assess how agricultural-nutrition linkages at the household level ($\frac{\partial y}{\partial F_A}$) vary depending on T, C and M. The assessment of hypotheses 1 and 2 accounts for the potential endogeneity of F_A and T. As is described below, the assessment of hypothesis 3 focuses on a cluster (village)-level technical efficiency indicator of A which can be considered exogenous.

3.1.1 Empirical specifications – IVGMM

The standard IVGMM models simply estimate

$$\begin{aligned} y_{h,i} = \beta_A A_h + \beta_T T_h + \beta_{AT} A_h \cdot T_h + \beta_{ACM} A_h \cdot g(C_h \cdot M_h) + \beta_{TCM} T_h \\ \cdot g(C_h \cdot M_h) + \beta_{ATCM} T_h \cdot g(C_h \cdot M_h) + \beta_Z Z_{h,i} + \varepsilon \end{aligned} \tag{12}$$

where h indicates household of individual i, $g(C_h \cdot M_h)$ is a function of the interaction of C_h and M_h. Practically, due to our modest sample sizes and multi-collinearity associated with high-dimensional interactions, we only consider the model where $g(C_h \cdot M_h) = C_h$ or $g(C_h \cdot M_h) = M_h$.

Potentially endogenous variables A_h, T_h, $A_h \cdot T_h$, and their interactions with $g(C_h \cdot M_h)$, are instrumented using $Z_{h,i}$, other excluded household-level IVs (Z_h^{IV}, described in a later section), and their interactions with $g(C_h \cdot M_h)$. Joint tests of endogeneity and Hansen's (1982) orthogonality test are conducted to assess the suitability of IVGMM and the set of excluded IVs.

3.1.2 Empirical specifications – NGPS-IPW

The NGPS-IPW method is as follows. To make the model estimable, we first split the samples into two groups by a set threshold level of APP, $\bar{A}$, that is, one sample with $A < \bar{A}$ and the other sample with $A > \bar{A}$. We then estimate probit regression to predict the propensity $\hat{p}$ that a household is with $A < \bar{A}$, or $A > \bar{A}$ given their observable characteristics $Z_{h,i}$ and Z_h^{IV}.

We then apply the generalized propensity score (GPS) method to T_h, as is described in Appendix A, and obtain a stabilized weight for w_h^T , based on the propensity that observed T_h is selected by the primary respondent (PR) of the household given their observable characteristics (Appendix A discusses the procedure more in detail).

We then estimate the following model through inverse probability weighted (IPW),

$$y_{h,i} = \beta_T^L T_h + \beta_C^L C_h + \beta_{CTT}^L T_h \cdot C_h + \beta Z_{h,i} \tag{13}$$

$$y_{h,i} = \beta_T^H T_h + \beta_C^H C_h + \beta_{CTT}^H T_h \cdot C_h + \beta Z_{h,i}$$

which are weighted least square (WLS) with weights $\widehat{w}_h = \frac{1}{\hat{p}} \cdot \frac{1}{w_h^T}$. This is an extension of GPS-IPW, which has been used in earlier studies (Imbens 2000; Bodnar et al. 2004; Flores & Mitnik 2013), to the framework of Huber (2014)'s nested propensity score method. It is "nested" as $\widehat{GPS}$ is also estimated using $1/\hat{p}$ as the weight.

Using the estimated coefficients, the statistically significant differences between β_{CTT}^L and β_{CTT}^H can then suggest that APP affects how the effects of cooking time on nutritional outcomes change given the cooking technologies. Specifically, if $\beta_{CTT}^L > \beta_{CTT}^H$, cooking time is complementary to APP at low C, but substituting at high C. If $\beta_{CTT}^L < \beta_{CTT}^H$, the opposite holds. We standardize the variables so that β_T^L and β_T^H provide the average returns to T_h given the available range of C_h.

We can also estimate the following by splitting the sample by half at sample median value of C instead of M:

$$\begin{aligned} y_{h,i} &= \beta_T^L T_h + \beta_M^L M_h + \beta_{MTT}^L T_h \cdot M_h + \beta Z_{h,i} \\ y_{h,i} &= \beta_T^H T_h + \beta_M^H M_h + \beta_{MTT}^H T_h \cdot M_h + \beta Z_{h,i}. \end{aligned} \tag{14}$$

If $\beta_{MTT}^L > \beta_{MTT}^H$, cooking time is complementary to APP at low M, but substituting at high M. If $\beta_{MTT}^L < \beta_{MTT}^H$, the opposite holds.

These methods are practical ways to show how the effects of APP on nutritional outcomes depend on cooking-time T, and how such relations change depending on cooking technologies and the level of market access.

Importantly, these approaches rely on the thresholds $\bar{A}$ that are selected. We check the robustness of our results by selecting slightly different $\bar{A}$.[6]

3.1.3 Technical efficiency

For testing hypothesis 3, we replace A with a technical efficiency score of agricultural production. We focus on variations of technical efficiency across clusters (villages) rather than across households. One reason for this is because common methodologies like DEA used for estimating technical efficiency tend to be susceptible to outliers and thus often perform better with cluster (village)-level median values.[7] Furthermore, technical efficiency can be significantly affected by the variations in agroecological conditions that tend to vary more across villages than within villages. For example, agricultural research and development that affects technical efficiency contributes to developing technologies suitable for particular areas, rather than for particular households.

The model for hypothesis 3 therefore proceeds by first estimating, through DEA, the technical efficiency score of agricultural production at the cluster where household h is located ($\widetilde{A_h}$), and estimates

$$\begin{aligned} y_{h,i} &= \gamma_A^L \widetilde{A_h} + \gamma_T^L T_h + \gamma_{AT}^L \widetilde{A_h} \cdot T_h + \gamma^L Z_{h,i} \text{ for low } C \text{ or } M \\ y_{h,i} &= \gamma_A^H \widetilde{A_h} + \gamma_T^H T_h + \gamma_{AT}^H \widetilde{A_h} \cdot T_h + \gamma^H Z_{h,i} \text{ for high } C \text{ or } M \end{aligned} \tag{15}$$

[6] Results are available from authors upon request.

[7] DEA is also suitable because it is particularly reliable in estimating efficiency where the markets for inputs and outputs are imperfect (Charnes et al., 1994), as is the case in rural areas in many developing countries.

which are WLS estimated using weights $\widehat{w} = \frac{1}{GPS}$. Note $\widehat{w}$ here does not include $1/\hat{p}$ because $\widetilde{A_h}$ is included as an exogenous variable. Then, coefficients on γ_{AT}^{L} and γ_{AT}^{H} inform whether technical efficiency in agricultural production and cooking time complement each other in improving nutritional outcomes.

Standard errors. Standard errors for models other than IVGMM are adjusted through a multi-stage paired bootstrap (Efron 1979; Freedman 1981), to take into account the fact that IPWs are predicted values.

4 Data and descriptive statistics

4.1 Data

Our analyses primarily use the household survey data collected by the International Food Policy Research Institute (IFPRI) in 2015 and 2018 in the Khatlon province, within the zone of influence (ZOI) of the United States Agency for International Development (USAID) Feed the Future project (IFPRI2015 and IFPRI2018 thereafter) (for details of IFPRI2015 and IFPRI2018, see IFPRI 2016, 2019; Takeshima et al. 2019).

IFPRI2015 data were collected partly for evaluating USAID's Feed the Future project in its ZOI, which consisted of 12 Raions (Districts) within Khatlon province (IFPRI 2016). In total, 2,000 households were selected. IFPRI2015 data were collected in February and March of 2015. The samples were selected through multiple-stage random sampling; at the first stage, 100 clusters were randomly selected based on the probability proportional to size among the list of enumeration areas based on the 2010 census (IFPRI 2016). From each cluster, twenty households were then randomly sampled.

Similarly, IFPRI2018 data were collected for the assessment of USAID's Feed the Future in the same 12 districts. However, IFPRI2018 focused more on the particular component of Tajikistan Agriculture and Water Activity (TAWA). A total of 80 villages were purposively selected from these 12 districts, from which 15 farm households were again purposively selected: 10 households among those who participated in TAWA capacity-building activities, and 5 households among the list of horticultural producers (IFPRI 2019). The findings from IFPRI2018 are therefore not representative and thus external validity to the rest of these districts needs to be assessed with caution. However, the sample characteristics of IFPRI2018 are somewhat different from those of IFPRI2015, and obtaining consistent results across the two datasets can suggest their robustness. In addition, since IFPRI2018 was collected from August to October 2018, a period very different from the season covered by IFPRI2015, the findings from both data offer important robustness checks. IFPRI2018 consists of 80 villages as sampling clusters. As was described above, technical efficiency is estimated using the village as the primary unit.

Among the total of 2,000 and 1,200 household samples in IFPRI2015 and IFPRI2018, our primary sample households consist of agricultural households, in which females reported cooking time as described below. This category covers 1,525 out of 2,000 households in IFPRI2015 and 1,033 out of 1,200 households in IFPRI2018, and thus these households are used in our analyses. These households include a total of 3,573 and 1,961 female members of reproductive age, respectively. Furthermore, IFPRI2015 households include 1,514 children and 594 children aged 6-59 months and 6-23 months, respectively. These individuals constitute the primary-sample individuals in our analyses.

These household data are combined using global positioning system coordinates with various spatial data on key agroclimatic and socioeconomic variables. The data on topography, including elevation and slope, are from the United States Geological Survey (USGS 1996), from which a terrain ruggedness index was constructed following Riley et al. (1999). A map of major rivers from Lehner et al. (2006) is used to calculate the Euclidean distance to the nearest major river. Underground water-table depth is obtained from Fan et al. (2013). Nighttime light data are obtained from NOAA (2019), while the distance to the nearest road is constructed using NASA (2019).

Time-use data. Time-use data are included in IFPRI2015 and IFPRI2018 and reported by a PR in the household, who are in most cases WRA aged 15-49. Time use data for different activities are reported as 24-hours recall data for each 15-minute segment. Activities are coded into 17 categories, among which "cooking" is one category. The methodology is generally consistent with the diary method based on 24-hour recall, described in time-use literature (Johnston et al. 2018). By using the 15-minute segment, our data may be somewhat more precise compared to some other studies. For example, 30 minutes interval was used by Esquivel et al. (2008) in South Africa.

4.2 Set of dependent and independent variables in each dataset

Because IFPRI2015 and IFPRI2018 were collected with somewhat different focuses, certain nutritional outcome variables (dependent variables) and independent variables appear only in one of the datasets. Furthermore, certain nutritional outcomes are reported only for specific age-groups. We, however, still use both datasets in our analyses because there is also substantial commonality between these datasets. Here we describe them, as well as the common and data-specific independent variables.

4.2.1 Variables on nutritional outcomes and APP, technical efficiency

Among the dependent variables used in our analyses, WDS and WDSM are reported in both data. Nutritional outcomes for children (CMAD, CMDD, WAZ, and WHZ) are only reported in IFPRI2015. Furthermore, CMDD and CMAD are only reported for children aged 6–23 months old, while WAZ and WHZ are reported for children 6–59 months old.

APP are reported for both IFPRI2015 and IFPRI2018. Technical efficiency is, however, estimable only in IFPRI2018, in which detailed information on production inputs use is reported along with APP.

4.2.2 Independent variables

The set of independent variables consist of factors associated with (a) household APP; (b) cooking time; (c) nutritional outcomes of individual women; (d) nutritional outcomes of individual children; and (e) intrahousehold variations of nutritional outcomes among women or children (household level). These consist of common household-level variables that are included as controls for all groups (a) – (e) for consistency and another specific set of variables that are included only in certain groups (a) – (e).

4.2.2.1 Common set of household-level variables

The common set of household-level variables includes basic household demographics, such as the average characteristics of working-age members (aged 15-60) like age and gender, household size by age and gender (elderly above 60, working-age 15-60, older children 6-14, and younger children under 6), and average years of formal education of working-age members, which also proxy the income status of household members.

A common set of household-level variables also include housing utility conditions, which can affect both nutritional conditions and APP (for example, agricultural labor productivity). These include whether improved materials are used for flooring and exterior walls, whether the household uses an improved source of drinking water and an improved sanitation system, and whether the community that hosts the household has centralized garbage collection and disposal systems and a centralized sewage system.[8] Values of durable assets owned (other than cooking equipment which is separately captured), and whether owning large livestock assets like cows, are also included.

Agroecological factors include elevation, topography (terrain ruggedness), and hydrological conditions (proximity to major rivers and groundwater depth). The surveyed area is relatively uniform in terms of other agroclimatic conditions like soils and rainfall, and other conditions like temperature are highly correlated with the aforementioned variables, and thus are not included as the set of variables.

Wealth variables include the per capita value of durable assets, and the ownership of a cow which is a key livestock animal. Ownership of refrigerators and freezers is also included to control for the storage life of food, either home produced or purchased. Access to finance is proxied by a variable which indicates whether any member of the household had obtained credit from the formal sector. The value of remittances received by households is included to capture external income flows.

Certain agricultural factors, such as the size of farm areas owned, the share of perennial crops, and the number of productive trees owned, are also included to control for the general demand for farm labor, which affects not only APP but also the nutritional demand of the household members.

For IFPRI2015, distance to the nearest food-market is also included. Since IFPRI2018 does not include this, we replaced it with distances to the nearest road and railway. For IFPRI2015, access to infrastructures and institutions include distances to the nearest state daycare, and whether the community had received inoculation campaigns is included as well. Information on average food price (average per kilogram of all 12 groups) is included to further control for the accessibility of food, particularly for the poor.

The VCE owned by the household is used to proxy cooking technologies, which can serve as wealth but also affect cooking time. The variable is measured as the total VCE in the household, including gas oven, electric oven, gas hob, electric hob, electric stove, electric water heater, outdoor metal stove (heating and cooking), kerosene stove, and wood stove.

Similarly, the nighttime light intensity is also included to capture the overall level of economic growth (Henderson et al. 2012) and urbanization effects on nutritional outcomes (Amare et al. 2018), which can affect the household-level ANL. As was described earlier, we estimate models differentiating households based on the cooking technologies and nighttime light intensity of their residing areas.

---

[8]Improved sources of drinking water include urban plumbing, rural plumbing, public tap/standpipe, hand pump and protected dug well or spring or rainwater, piped water into the dwelling, piped water into the yard, or a tube well/borehole, as classified by WHO & UNICEF (2006). An improved sanitation system includes toilet facilities that are flush/pour-flush connected to a piped sewage system or septic tank, or a latrine connected to a septic tank, composting toilet, ventilated improved pit latrine, or a pit latrine with a slab (WHO & UNICEF 2006).

4.2.2.2 (a) Factors affecting APP – also used as IV for APP in IVGMM

Following Takeshima et al. (2019), which investigates similar household-level ANL but without the focus on cooking time, we include agricultural capital, as well as access to extension, as factors affecting only APP but not nutritional outcomes or cooking time, once other variables are controlled for. Specifically, agricultural capital is proxied by whether the household owned tractors and the number of other non-tractor agricultural equipment. Extension access is proxied by whether the communities receive government extension visits (for IFPRI2015) and whether any household members received extension advice (for IFPRI2018).

4.2.2.3 (b) Factors associated with cooking-time variables

These variables include those that may be associated with the time-use, as well as the self-selection of a respondent within the household (since one respondent was selected within the household to answer about her time use in the previous day).[9]

These variables include the age and education (which proxy income status) of the PR, as well as their averages among WRA; number of older, younger, or same-age members relative to PR (by gender); number of children being taken care of by the PR (by gender) and the number of all children being taken care of by all WRA (by gender); whether there are any other adult women in the household without children to take care of (and thus who can serve as helpers); whether the PR is pregnant / lactating; and the number of all WRA who are pregnant / lactating. We also control for the expenditures on domestic services (payment for non-member staff providing childcare and babysitting, among others) which can partly affect PR's time-use.

4.2.2.4 (c) Factors associated with individual children's nutritional outcomes

For children 6-59 months, these variables include age and gender and birth quarter, as well as the caregiver's age and education. Past studies often suggest that the effect of mother's time use on child nutritional outcomes may depend on the age of the child (Coreil 1991; Ricci et al. 1996; Paolisso et al. 2002). Twelve-month precipitation during the pre-born period is also included to capture the effects of prenatal environmental conditions (Shively et al. 2015). For children 6-23 months, birth order is also included, which is found to affect nutritional outcomes in certain social contexts (for example, Jayachandran & Pande 2017).

4.2.2.5 (d) Factors associated with individual women's nutritional outcomes

Individual women's characteristics include age, education, whether pregnant or lactating, and social status (whether married / in-union, divorced, separated, or widowed) (Harris-Fry et al. 2017).

4.2.2.6 (e) Factors associated with intrahousehold factors

Factors associated with intrahousehold variations include various aspects of average and variations in individual women's and children's characteristics in the household. These include the average and standard deviations in age; years of education of WRA in the household; and age of children (among children 6-59 months) in the household, as well as the share of girls among

---

[9]Controlling for the characteristics of respondents reporting time use is important not only because of self-selection. It is also because individual characteristics can be important determinants of time use; such determinants include marital status, whether having children or not, and the age / seniority of women (Zycherman 2013). The presence of other care-taking women in households can also allow particular women to devote more time to other activities like work or cooking (Zycherman 2013; Nti et al. 1999).

these children; and average and variations in birth quarters among these children. We also include the average and variations of the ages and years of education of all caregivers in the household.[10]

4.2.3 Natural log transformation

To remain consistent, we avoid transforming independent variables as much as possible. However, variables with extremely high skewness (greater than 10), are natural-log transformed, as doing so is found to lead to more stable results.

4.3 Descriptive statistics

Table 1 through Table 4 provide descriptive statistics of the household-level variables and individual characteristics of women and children being studied. In both IFPRI2015 and IFPRI2018, the households being studied are generally smallholders, owning less than 1 ha of farmland, producing 2–3 groups of crops, generally asset poor, living in limited-quality houses, and located in rural areas. On average, however, household members have modest education levels, having completed on average 10 years of formal education.

[Insert Table 1 here]
[Insert Table 2 here]
[Insert Table 3 here]
[Insert Table 4 here]

While these characteristics generally hold for IFPRI2015 and IFPRI2018 samples, there are some differences: the households in the former data have a somewhat larger household size, with poorer housing conditions. The findings from both datasets will therefore demonstrate some robustness across different types of households.

5 Results

Our primary interests are on the interactive effects of APP and PR's cooking time on nutritional outcomes and how they vary depending on the household's cooking technologies (proxied by VCE) and market access (proxied by nighttime light intensity). Other individual results are of secondary importance. We therefore first briefly discuss the factors associated with APP and cooking time and discuss the main results more in detail.

5.1 Factors associated with APP and cooking time

Table 16 and Table 17 in Appendix B summarize the results of the first-stage probit on APP and the GPS model on cooking time, respectively. These regressions are reduced form and do not suggest any structural relations. Generally, whether the household exceeds the median

[10]Various studies suggest the variations on nutritional outcomes among women within the households depending on their demographic characteristics. For example, older women tend to be associated with greater weight and higher body mass index (BMI) (Hasan et al. 2017; Beal et al. 2018) while younger women are more likely to suffer from different types of nutritional deficiencies. Sometimes, the relationship is more complex, as the challenge of the double burden of malnutrition is also more likely among older women than in younger women (Oddo et al. 2012). These patterns also do not always hold everywhere. Older women are found to eat somewhat healthier in Viet Nam (Nguyen et al. 2018) and are more at risk of underweight in Bangladesh (Khanam et al. 2018). Sometimes, older women also pass down nutrition knowledge to younger women (Dillon et al. 2019), which can potentially mitigate severe inequality in nutritional outcomes among women in the household.

level of APP is associated with the ownership of cows, farm size, and number of non-tractor agricultural equipment owned. ADS is also positively associated with agroclimatic conditions and the share of the perennial crop area. The number of productive trees owned is positively associated with ADS but is negatively associated with APV, possibly because tree crops may lead to diversification away from field crops but may also experience trade-offs in the overall production scale. ADS and APV are also positively associated with distance from the nearest food market. While this may seem counter-intuitive, this may be because we also condition on other general measurements of market access like nighttime; distance, particularly to the food-market, may actually encourage household food production, conditional on access to the more general market. ADS and APV are also significantly associated with household demographics, housing conditions, and sanitation infrastructure, indicating somewhat complex mechanisms affecting households' APP.

Similarly, cooking time by the PR is generally associated with household demographics, housing conditions, and cow ownership, among other factors. Cooking time tends to be shorter among older PRs, but also if there are more other females in the household who may be able to help in cooking (particularly females who are not taking care of any children). Cooking time by PR is also associated with the general characteristics of WRA in the households, suggesting that the model captures the effect of self-selection on who becomes PR in the household.

Table 5 and Table 6 show the relevant balancing properties achieved through IPW and GPS-IPW, respectively. Table 5 shows the share (%) of variables that are unbalanced between two samples separated, in terms of the statistical significance of the differences in sample means, by the median value of APP. In raw samples, means are generally significantly different between low-APP and high-APP samples (indicating the lack of balance) for almost half of the variables, at 5 and 10 percent significance levels. However, once IPW-adjusted, less than 2 and 4 percent of variables show a significant difference in means, which would be expected under the null hypothesis of balanced samples. Satisfactory balancing properties suggest that the differences within any differences in nutritional outcomes can be attributed to APP itself, instead of any other observable variables.

[Insert Table 5 here]
[Insert Table 6 here]

Table 6 suggests that the GPS model estimation fails to reject the normality of the residuals, which is important for consistency. Furthermore, in a similar way to Table 5, the balancing properties are satisfied based on the tests described in Appendix A; approximately 5 to 10 percent of variables exhibit t-tests thresholds of corresponding statistical significance, which is to be expected under the null hypothesis that means of covariates are jointly equal across groups. These diagnostic tests indicate that household characteristics are similar within each subgroup, conditional on the estimated GPS, and thus we can consistently identify the effects of cooking time on nutritional outcomes in subsequent regressions.

5.2 Main results

Our main results on the interactive effects of APP and cooking time are presented in Table 7 through Table 13. These tables summarize the coefficients on the variables of our main interests, interactive effects of cooking time with APP, on a range of nutritional outcomes. Effects of cooking time in general (apart from interaction with APP, etc.) are found to be generally ambiguous and insignificant, and therefore we focus on presenting the interaction effects with APP. The detailed results for the main models are presented in Appendix B Table 18.[11]

NGPS-IPW results. Table 7 shows three types of figures. Columns (A) show how an increase in APP (from below-median level to above-median level) affects the marginal effects of (a one-standard-deviation increase in) cooking time on nutritional outcomes. Columns (B) show how the effects in columns (A) vary depending on the VCE of the household. Specifically, columns (B) show the changes in the columns (A) entries caused by a one-standard-deviation change in VCE. Similarly, columns (C) show how the effects in columns (A) vary depending on a one-standard-deviation increase in the nighttime light intensity. For example, a figure of 1.248 in the first column (A) in the first row means that, an increase in ADS from below-median to above-median increases the effects of a one-standard-deviation increase in cooking time on WDS by 1.248. This figure is the average across all VCE in the sample of low nighttime light intensity area. A figure of -.323 in column (B) in the first row means that these ADS-cooking-time interactive effects averaged in column (A) are negatively related to VCE; specifically, these ADS-cooking-time interactive effects on WDS increase (decline) by 0.323 as the VCE of the household decreases (increases) by one-standard deviation. These results together suggest that, in areas with low nighttime light intensity, a longer cooking time by the household significantly increases the positive effects of ADS on WDS as the household's VCE declines. In other words, there is positive complementarity between ADS and the household's cooking time, if the household has lower cooking technologies and is in more rural areas.

[Insert Table 7]

As can be seen, negatively significant figures in columns (B) and in columns (C) suggest that there is more positive complementarity between APPs and household's cooking time in households with lower VCE and in more rural areas, respectively. These conditions generally seem to hold for quite a few nutritional outcomes and APPs (particularly ADS). At the same time, columns (A) are generally insignificant, suggesting that, on average, household cooking time and APPs are neither complementary nor substitutes. Therefore, where (B) or (C) are significantly negative, APP and cooking time are likely to be strictly complementary with lower VCE or lower nighttime light intensity.

Table 8 presents similar sets of results but for the effects on intrahousehold inequality in nutritional outcomes among women and children. Many figures are statistically insignificant, suggesting that cooking time generally does not affect how APPs change the inequality in nutrition. Certain figures are negative and modestly significant, such as column (A) for ADS-WAZ linkage and column (B) for ADS-WDS linkages. In these cases, longer cooking time may generally reduce the effects of APPs on inequality and particularly so in households with lower VCE. It is remarkable that no such patterns are observed for opposite directions. Altogether, a longer cooking time by the household may modestly shift ANL toward being equality-enhancing, in rural areas with low cooking technologies where nutrition insecurity may be the most severe.

[11]Detailed results for the remaining specifications are available from authors upon request.

[Insert Table 8]

IVGMM results. Table 9 and Table 10 summarize the set of results related to Table 7 and Table 8 but are estimated through IVGMM. Table 11 and Table 12 summarize the diagnostic statistics of these IVGMM estimates, which generally show that models are strongly identified and orthogonality conditions are satisfied, suggesting the consistency of the results.

[Insert Table 9]
[Insert Table 10]
[Insert Table 11]
[Insert Table 12]

Table 9 shows the estimated results in 2-by-2 format, differentiated by nighttime light intensity and VCE. For example, 0.790 means that, for households with low nighttime light intensity and low VCE, a one-standard-deviation increase in household cooking time increases the effects of a one-standard-deviation increase in ADS on WDS by 0.790, suggesting the complementarity between cooking time and ADS. This effect diminishes for households residing in a similarly low nighttime light intensity area but with higher VCE (insignificant -.050), or households residing in a high nighttime light intensity area. The finding that the complementarity between ADS and household cooking time is stronger in areas with low nighttime light intensity and for households with low VCE is consistent with the findings based on NGPS-IPW in Table 7.

Table 10 summarizes the set of results related to Table 8 (effects on intrahousehold inequality) but are estimated through IVGMM. For example, -0.346 means that, for households in areas with low nighttime light intensity, a one-standard-deviation increase in household cooking time *decreases* the effects of ADS on WDS inequality by 0.346, suggesting the complementarity between cooking time and ADS in reducing intrahousehold inequality in WDS. Overall, these effects are stronger in areas with low nighttime light intensity and diminish (or become more inequality-increasing) in areas with higher nighttime light intensity, particularly for WDS and WAZ. These patterns are generally consistent with Table 8, suggesting the robustness.

Table 13 summarizes similar results as above, but with the focus on technical efficiency in agriculture instead of APP. As was described above, these results for technical efficiency are provided only for IFPRI2018 due to data availability. Interpreted in similar ways as for Table 7 through Table 10, Table 13 suggests the following: higher technical efficiency and longer cooking time are generally complementary in improving WDS, especially in areas with low nighttime intensity and for households with lower VCE, without affecting intrahousehold inequality of WDS.

[Insert Table 13]

Summary patterns of results from Table 7 through Table 13. Table 14 and Table 15 summarize the general patterns of results from Table 7 through Table 13, focusing on the directions of the joint effects of APP or technical efficiency and household's cooking time on nutritional outcomes or their intrahousehold inequality. Furthermore, the effects of reduced nighttime light intensity and reduced VCE are also summarized.

[Insert Table 14]
[Insert Table 15]

Overall, we see that the results are moderately consistent with our aforementioned three hypotheses. Households' cooking time tends to complement the ANL at the household level. This effect is stronger in areas with low nighttime light intensity and for households with low VCE. Because of limited market access for food and cooking technologies (as well as cooking services), a household's self-production of food and cooking activities are important determinants of nutrition. Furthermore, increased self-production of food and cooking generally does not affect intrahousehold inequality in nutritional outcomes among women or children, and if they do, they mitigate such inequality, especially for households with limited market access and cooking technologies.

These results are relatively robust against the use of different methodologies (IPW vs. IVGMM) and different datasets for outcomes like WDS. While the results are not always statistically significant and thus suggest some weaknesses in the evidence, they are robust against alternative hypotheses (hypotheses in opposite directions) for a range of nutritional outcomes and APPs or technical efficiency.

6 Conclusions

Household-level ANL has been found to be generally more important for nutrition improvement in rural subsistence systems, where access to the market is generally limited for food items. While such subsistence systems are also often characterized by failures of markets for other goods and services, their effects on the characterization of ANL have not been studied widely. For example, markets for food processing services may also be imperfect and therefore household's self- investments in cooking time may become important factors affecting ANL.

Using the primary data in Tajikistan, we find moderate evidence that a longer time dedicated to cooking by women in the household enhances household-level ANL for a range of nutritional outcomes, including dietary diversity of women and children and body weights of children. Furthermore, these factors tend to sometimes mitigate intrahousehold inequality in nutritional outcomes among these women and children, conditional on the variations of individual characteristics. These effects are stronger in areas with lower nighttime light intensity and for households with lower values of cooking assets. Lastly, raising technical efficiency is likely to be important when aiming for nutrition improvement through household-level ANL.

These findings do not directly inform necessary interventions to affect cooking time or cooking technologies, since these decisions may be endogenous to various other factors that affect time use and asset investments. However, these findings offer richer insights into the characteristics of ANL. Findings are consistent with the economic characteristics of the subsistence system, where households are in more autarkic regimes. ANL is relatively strong in such a subsistence system, as has been shown in many aforementioned studies but also depends on households' self-production of complementary inputs, one example of which is cooking. Since time (labor) is one of the important resources owned by poor households with nutrition insecurity, cooking time symbolizes the significant resource requirements involved with operationalizing household-level ANL. These findings underscore the importance of valuing non-market labor supply, especially by women, in improving nutrition through ANL. Reliance on the self-production of cooking activities at home also suggests some vulnerability of ANL. The linkage is less susceptible to market risks, but more susceptible to, for example, health shocks of those engaged in cooking at home or other shocks that affect their labor availability for cooking. Overall, our findings underscore the importance of understanding ANL as part of a broader rural subsistence framework.

References

Allen, L., and S. Gillespie. 2001. *What Works? A Review of the Efficacy and Effectiveness of Nutrition Interventions.* Geneva: United Nations Administrative Committee on Coordination Sub-Committee on Nutrition; Asian Development Bank.

Amare, M., C. Arndt, K. A. Abay, and T. Benson. 2018. "Urbanization and Child Nutritional Outcomes." *World Bank Economic Review*, October 10.

Azzarri, C., and A. Zezza. 2011. "International Migration and Nutritional Outcomes in Tajikistan." *Food Policy* 36 (1): 54-70.

Bamji, M. S., and B. V. S. Thimayamma. 2000. "Impact of Women's Work on Maternal and Child Nutrition." *Ecology of Food and Nutrition* 39 (1): 13-31.

Barro, R., and J. W. Lee. 2013. "A New Data Set of Educational Attainment in the World, 1950–2010." *Journal of Development Economics* 104: 184-198.

Beal, T., A. Tumilowicz, A. Sutrisna, D. Izwardy, and L. M. Neufeld. 2018. "A Review of Child Stunting Determinants in Indonesia." *Maternal & Child Nutrition* 14 (4): e12617.

Becker, G. 1965. "A Theory of the Allocation of Time." *Economic Journal* 75 (299): 493-517.

Bhandari, S., J. T. Sayami, P. Thapa, M. Sayami, B. P. Kandel, and M. R. Banjara. 2016. "Dietary Intake Patterns and Nutritional Status of Women of Reproductive Age in Nepal: Findings from a Health Survey." *Archives of Public Health* 74 (2): 1-11.

Bia, M., and A. Mattei. 2008. "A Stata Package for the Estimation of the Dose-Response Function through Adjustment for the Generalized Propensity Score." *Stata Journal* 8 (3): 354-373.

Blau, D. M., D. K. Guilkey, and B. M. Popkin. 1996. "Infant Health and the Labor Supply of Mothers." *Journal of Human Resources* 31 (1): 90-139.

Bodnar, L. M., M. Davidian, A. M. Siega-Riz, and A. A. Tsiatis. 2004. "Marginal Structural Models for Analyzing Causal Effects of Time-Dependent Treatments: An Application in Perinatal Epidemiology." *American Journal of Epidemiology* 159 (10): 926-934.

Charnes, A., W. Cooper, A. Lewin, and L Seiford. 1994. *Data Envelopment Analysis: Theory, Methodology, and Applications.* New York: Springer Science & Business Media.

Coreil, J. 1991. "Maternal Time Allocation in Relation to Kind and Domain of Primary Health Care." *Medical Anthropology Quarterly* 5 (3): 221-235.

Davidson, R., and J. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.

Deaton, A. 1995. "Data and Econometric Tools for Development Analysis." In *Handbook of Development Economics.* Vol. 3, Part A, edited by J. Berhman and T. N. Srinivasan, 1785-1874. Amsterdam: North Holland.

Dillon, A., J. Arsenault, and D. Olney. 2019. "Nutrient Production and Micronutrient Gaps: Evidence from an Agriculture-Nutrition Randomized Control Trial." *American Journal of Agricultural Economics* 101 (3): 732-752.

Efron, B. 1979. "Bootstrap Methods: Another Look at the Jackknife." *Annals of Statistics* 7: 101-118.

Esquivel, V., D. Budlender, N. Folbre, and I. Hirway. 2008. "Explorations: Time-Use Surveys in the South." *Feminist Economics* 14 (3): 107-152.

Fan, Y., H. Li, and G. Miguez-Macho. 2013. "Global Patterns of Groundwater Table Depth: A Stochastic Model of Applied Research." *Science* 339: 940-943.

Fan, S., S. Yosef, and R. Pandya-Lorch. 2019. *Agriculture for Improved Nutrition: Seizing the Momentum*. Washington, DC: International Food Policy Research Institute.

FAO (Food and Agricultural Organization of the United Nations) and FHI 360. 2016. *Minimum Dietary Diversity for Women: A Guide for Measurement.* Rome: FAO.

Finaret, A. B., L. C. Miller, N. Joshi, S. Mahato, M. Lohani, J. Drozdowsky, and B. L. Rogers. 2018. "Longitudinal Analysis of the Intrahousehold Distribution of Foods in Rural Nepal: Relative Variability of Child Dietary Quality across Age and Sex Cohorts." *Food Policy* 79: 101-110.

Flores, C. A., and O. A. Mitnik. 2013. "Comparing Treatments across Labor Markets: An Assessment of Nonexperimental Multiple-Treatment Strategies." *Review of Economics and Statistics* 95 (5): 1691-1707.

Freedman, D. 1981. "Bootstrapping Regression Models." *Annals of Statistics* 9: 1218-1228.

Haddad, L., J. Hoddinott, and H. Alderman. 1997. *Intrahousehold Resource Allocation in Developing Countries*. Baltimore: Johns Hopkins University Press.

Hasan, M., I. Sutradhar, A. S. M. Shahabuddin, and M. Sarker. 2017. "Double Burden of Malnutrition among Bangladeshi Women: A Literature Review." *Cureus* 9 (12): 1-8.

Harris-Fry, H. A., N. Shrestha, A. Costello, and N. M. Saville. 2017. "Determinants of Intra-household Food Allocation between Adults in South Asia – A Systematic Review." *International Journal for Equity in Health* 16 (107): 1-21.

Harris-Fry, H. A., P. Paudel, N. Shrestha, T. Harrisson, B. J. Beard, S. Jha, B. P. Shrestha, et al. 2018. "Status and Determinants of Intra-household Food Allocation in Rural Nepal." *European Journal of Clinical Nutrition* 72: 1524-1536.

Henderson, V. J., A. Storeygard, and D. N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review* 102: 994-1028.

Hirano, K., and G. Imbens. 2004. "The Propensity Score with Continuous Treatments." In *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives,* edited by A. Gelman and X. L. Meng, 73-84. Chichester, UK: John Wiley & Sons.

Hirvonen, K., and J. Hoddinott. 2017. "Agricultural Production and Children's Diets: Evidence from Rural Ethiopia." *Agricultural Economics* 48 (4): 469-480.

Howson, C. P., E. Kennedy, and A. Horwitz. 1998. *Prevention of Micronutrient Disorders: Tools for Policymakers and Public Health Workers.* Washington, DC: National Academic Press.

Huber, M. 2014. "Identifying Causal Mechanisms (Primarily) Based on Inverse Probability Weighting." *Journal of Applied Econometrics* 29 (6): 920-943.

IFPRI (International Food Policy Research Institute). 2016. *Feed the Future Tajikistan 2015: Zone of Influence Interim Assessment Report.* Washington, DC.

IFPRI (International Food Policy Research Institute). 2019. *Feed the Future Tajikistan 2018: Zone of Influence Interim Assessment Report.* Washington, DC.

Imbens, G. W. 2000. "The Role of the Propensity Score in Estimating Dose-Response Functions." *Biometrika* 87 (3): 706-710.

Jayachandran, S., and R. Pande. 2017. "Why Are Indian Children So Short? The Role of Birth Order and Son Preference." *American Economic Review* 107 (9): 2600-2629.

Johnston, D., S. Stevano, H. J. Malapit, E. Hull, and S. Kadiyala. 2018. "Time Use as an Explanation for the Agri-nutrition Disconnect? Evidence from Rural Areas in Low and Middle-Income Countries." *Food Policy* 76: 8-18.

Jones, A. D. 2017. "Critical Review of the Emerging Research Evidence on Agricultural Biodiversity, Diet Diversity, and Nutritional Status in Low- and Middle-Income Countries." *Nutrition Reviews* 75 (10): 769-782.

Khanam, R., A. S. C. Lee, M. Ram, M. A. Quaiyum, N. Begum, A. Choudhury, P. Christian, L. C. Mullany, and A. H. Baqui. 2018. "Levels and Correlates of Nutritional Status of Women of Childbearing Age in Rural Bangladesh." *Public Health Nutrition* 21 (16): 3037-3047.

Klassen, A. C., B. J. Milliron, Y. Suehiro, S. Abdulloeva, B. Leonberg, S. Grossman, M. Chenault, L. Bossert, J. Maqsood, R. Abduzhalilov, and M. Iskandari. 2018. " 'Then You Raise Them with Shirchoy or Cookies': Understanding Influences on Delayed Dietary Diversity among Children in Tajikistan." *Maternal & Child Nutrition* 15 (2): 1-11.

Kluve, J., H. Schneider, A. Uhlendorff, and Z. Zhao. 2007. *Evaluating Continuous Training Programs Using the Generalized Propensity Score*. IZA Discussion Paper 3255. Bonn, Germany: Institute for the Study of Labor.

Komatsu, H., H. J. L. Malapit, and S. Theis. 2018. "Does Women's Time in Domestic Work and Agriculture Affect Women's and Children's Dietary Diversity? Evidence from Bangladesh, Nepal, Cambodia, Ghana, and Mozambique." *Food Policy* 79: 256-270.

Kumar, N., J. Harris, and R. Rawat. 2015. "If They Grow It, Will They Eat and Grow? Evidence from Zambia on Agricultural Diversity and Child Undernutrition." *Journal of Development Studies* 51 (8): 1060-1077.

Lehner, B., K. Verdin, and A Jarvis. 2006. *HydroSHEDS Technical Documentation.* Washington, DC: World Wildlife Fund US.

Mukhamedova, N., and K. Wegerich. 2018. "The Feminization of Agriculture in Post-Soviet Tajikistan." *Journal of Rural Studies* 57: 128-139.

NASA (National Aeronautics and Space Administration). 2019. Global Roads Open Access Data Set (gROADS), v1 (1980−2010). Accessed October 25, 2019. https://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1/data-download.

Nguyen, C., D. Hoang, P. Nguyen, A. Ha, T. Chu, N. Pham, A. H. Lee, D. V. Duong, and C. Binns. 2018. "Low Dietary Intakes of Essential Nutrients during Pregnancy in Vietnam." *Nutrients* 10 (8): 1025.

NOAA (National Oceanic and Atmospheric Administration). 2019. *Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB)*. Boulder, CO, US: Earth Observation Group, NOAA National Centers for Environmental Information (NCEI).

Nti, C. A., D. Inkumsah, and G. Fleischer. 1999. "Influence of Women's Workload on their Nutritional Status in Selected Communities in Ghana." *Journal of Consumer Studies & Home Economics* 23 (3): 165-170.

Oddo, V. M., J. H. Rah, R. D. Semba, K. Sun, N. Akhter, M. Sari, S. de Pee, et al. 2012. "Predictors of Maternal and Child Double Burden of Malnutrition in Rural Indonesia and Bangladesh." *American Journal of Clinical Nutrition* 95 (4): 951-958.

Paolisso, M. J., K. Hallman, L. Haddad, and S Regmi. 2002. "Does Cash Crop Adoption Detract from Child Care Provision? Evidence from Rural Nepal." *Economic Development and Cultural Change* 50 (2): 313-338.

Pitt, M. M., M. R. Rosenzweig, and M. N. Hassan. 1990. "Productivity, Health, and Inequality in the Intrahousehold Distribution of Food in Low-Income Countries." *American Economic Review* 80 (5): 1139-1156.

Ricci, J. A., N. W. Jerome, I. Sirageldin, H. Aly, W. Moussa, O. Galal, G. G. Harrison, and A. Kirksey. 1996. "The Significance of Children's Age in Estimating the Effect of Maternal Time Use on Children's Well-Being." *Social Science & Medicine* 42 (5): 651-659.

Riley, S. J., S. D. DeGloria, and R. Elliot. 1999. “A Terrain Ruggedness Index That Quantifies Topographic Heterogeneity.” *Intermountain Journal of Sciences* 5 (1-4): 23-27.
Ruel, M. T., A. R. Quisumbing, and M. Balagamwala. 2018. “Nutrition-Sensitive Agriculture: What Have We Learned So Far?” *Global Food Security* 17: 128-153.
Shively, G., C. Sununtnasuk, and M. Brown. 2015. “Agricultural Diversity and Child Stunting in Nepal.” *Health Place* 35: 37-51.
Takeshima, H., R. Adhikari, S. Shivakoti, B. D. Kaphle, and A. Kumar. 2017. “Heterogeneous Returns to Chemical Fertilizer at the Intensive Margins: Insights from Nepal.” *Food Policy* 69: 97-109.
Takeshima, H., K. Akramov, A. Park, J. Ilyasov, Y. Liu, and T. Ergasheva. 2019. “Agriculture–Nutrition Linkages in Tajikistan: Evidence from Household Survey Data.” *Agricultural Economics,* forthcoming.
USGS (U.S. Geological Survey). 1996. *GTOPO30 (Global Digital Elevation Model).* Sioux Falls, SD, US: USGS Center for Earth Resources Observation and Science.
Weinberger, K., and I. Swai. 2006. “Consumption of Traditional Vegetables in Central and Northeastern Tanzania.” *Ecology of Food and Nutrition* 45 (2): 87-103.
Wood, E. A., K. McNamara, A. Kowalewska, and N. Ludgate. 2018. “Household Decision-making around Food in Rural Tajikistan: A Cross-Sectional Study to Help Extension Workers in the Field.” *Food & Nutrition Research* 62: 1-12.
WHO (World Health Organization) and UNICEF (United Nations Children’s Fund). 2006. *WHO Child Growth Standards and the Identification of Severe Acute Malnutrition in Infants and Children*. Geneva: World Health Organization; New York: UNICEF.
WHO (World Health Organization). 2010. *Indicators for Assessing Infant and Young Child Feeding Practices. Part 2: Measurement.* Geneva: WHO. https://www.who.int/nutrition/publications/infantfeeding/9789241599290/en/.
World Bank. 2007. *From Agriculture to Nutrition: Pathways, Synergies, and Outcomes.* Washington, DC: Agriculture and Rural Development Department, World Bank.
World Bank. 2019. *World Development Indicators*. Washington DC.
Zycherman, A. 2013. “The Changing Value of Food: Localizing Modernity among the Tsimane Indians of Lowland Bolivia.” PhD dissertation, Columbia University, New York.

Table 1. Descriptive statistics (household-level variables)

Variables	2015 (sample = 1,525)		2018 (sample = 1,033)	
	Mean	Std. dev	Mean	Std. dev
Agricultural production practices				
ADS	2.51	1.27	2.89	1.33
APV (2007 Somoni)	4395.09	16263.96	6631.64	30977.06
General household-level characteristics (including variables associated with inequality in women's nutritional outcomes)				
Average age of working-age members	35.16	6.47	33.65	5.89
Share of females among working-age members	0.52	0.14	0.53	0.16
Household size (female above 61)	0.20	0.41	0.13	0.34
Household size (female, 15-60)	2.46	1.28	1.89	1.02
Household size (female, 6-14)	0.75	0.93	0.53	0.81
Household size (female below 6)	0.75	1.01	0.38	0.68
Household size (male above 61)	0.21	0.41	0.13	0.34
Household size (male, 15-60)	2.32	1.30	1.67	1.09
Household size (male, 6-14)	0.76	0.89	0.50	0.79
Household size (male below 6)	0.77	1.02	0.35	0.65
Average years of formal education of working-age members (years)	10.01	1.76	10.60	1.48
Durable assets (somoni)	3736.15	15005.57	4680.62	12181.53
Improved sanitation (yes = 1)	0.03	0.16	0.03	0.17
Finished floor (yes = 1)	0.51	0.50	0.79	0.41
Finished wall (yes = 1)	0.13	0.34	0.45	0.50
Improved water source (yes = 1)	0.56	0.50	0.46	0.50
Own cows (yes = 1)	0.58	0.49	0.25	0.43
Altitude (meter)	413.01	103.63	423.74	84.92
Euclidean distance to the river (geographical minutes)	0.015	0.010	0.014	0.009
Groundwater depth (meters)	13.55	18.25	12.56	13.85
Terrain ruggedness index	50.84	89.01	35.15	44.96
Obtained credit (yes = 1)	0.09	0.28	0.28	0.45
Share of perennial crop area	0.24	0.24	0.13	0.28
Remittances received in a year (somoni)	1948.11	6350.25	1540.76	10129.38
Owned farm area (hectares)	0.84	5.05	0.72	1.77
Number of productive trees owned	2.15	30.39	18.79	116.70
Food price (average per kilogram of all 12 groups, somoni)	1.03	0.19	0.99	0.12
Own refrigerator, freezer (yes = 1)	0.32	0.47	0.56	0.50
Value of cooking equipment (somoni)	140.49	244.36	104.35	202.47
In community with centralized garbage collection (yes = 1)	0.06	0.23		
In community with centralized sewage system (yes = 1)	0.03	0.18		
Nighttime light index	8.31	6.01	9.01	5.60
Distance to nearest food market—average of all types (minutes)	24.84	106.30		
Distance to the nearest state daycare (km)	9.24	10.54		
Whether the community had received inoculation campaigns (yes = 1)	0.90	0.30		
Distance to road (Euclidean distance)			0.03	0.04
Distance to railroad (Euclidean distance)			0.04	0.03
Other female members (15-60) without caretaken children	1.37	1.21	2.02	1.07
Expenditure on non-member helpers (2007 Somoni)	0.66	14.35		
Average age of all WRA	29.80	6.76	30.65	7.60
Average education of all WRA	9.32	2.52	10.17	2.20
Number of caretaken children by all WRA	0.54	0.65		
Number of caretaken boys by all WRA	0.26	0.43		
Number of pregnant WRA	0.07	0.20		
Number of lactating WRA	0.16	0.29		
Whether owing tractors (yes = 1)	0.04	0.20	0.02	0.14

Variables	2015 (sample = 1,525)		2018 (sample = 1,033)	
	Mean	Std. dev	Mean	Std. dev
Number of other types of agricultural equipment owned	0.58	0.91	0.28	0.73
Whether receiving extension advice (yes = 1)			0.05	0.22
Whether the community receives government extension visit (yes = 1)	0.59	0.49		
<u>*Characteristics of PR*</u>				
PR's age	42.96	12.32	40.60	11.89
PR's education	9.85	2.74	10.27	2.29
Number of caretaken children by PR	0.32	0.69		
Other members older than PR (male)	1.02	0.80	0.91	0.63
Other members older than PR (female)	0.37	0.68	0.25	0.54
Other members younger than PR (male)	3.04	2.07	1.80	1.48
Other members younger than PR (female)	2.86	2.09	1.74	1.46
Other members same age as PR (male)	0.09	0.29	0.09	0.28
Other members same age as PR (female)	0.01	0.10	0.01	0.07
Whether PR is pregnant	0.03	0.16		
Whether PR is lactating	0.10	0.30		

Source: Authors.

Note: ADS = agricultural diversity score; PR = primary respondent of the household; APV = agricultural production values; WRA = women of reproductive age.

Table 2. Descriptive statistics of household-level variables associated with the inequality of children's nutritional outcomes (IFPRI2015 only)

Variables	Sample size = 439	
	Mean	**Std. dev**
Age of children 6-59 months (average in the household, days)	807.90	267.49
Age of children 6-59 months (SD in the household, days)	504.52	223.99
Share of girls among children 6-59 months in the household	0.51	0.32
Age of caregivers of children (average in the household)	29.42	8.58
Age of caregivers of children (SD in the household)	2.31	4.25
Education year of caregivers of children (average in the household)	9.53	1.62
Education year of caregivers of children (SD in the household)	0.92	0.88
Birth quarters of children (average in the household)	2.90	0.18
Birth quarters of children (# of different birth quarters)	0.25	0.11

Source: Authors.

Note: SD = Standard deviation.

Table 3. Descriptive statistics of variables for individual woman respondent

Variables	2015 N = 3,573		2018 N = 1,961	
	Mean	Std. dev	Mean	Std. dev
Woman's age (year)	28.26	9.51	28.89	9.59
Woman's education (years completed)	2.49	2.26	10.20	2.36
Age order within the household	4.47	2.25	3.64	1.92
Age order within the household (among females)	1.48	1.24	1.06	1.06
Pregnant (yes = 1)	0.07	0.26		
Lactating (yes = 1)	0.15	0.36		
Marital status – in consensual union (yes = 1)	0.28	0.45		
Marital status – divorced (yes = 1)	0.01	0.10		
Marital status – separated (yes = 1)	0.01	0.04		
Marital status – widow (yes = 1)	0.01	0.12		
Number of caretaken children by the woman	0.51	0.79		
Number of caretaken boys by the woman	0.26	0.53		

Source: Authors.

Table 4. Descriptive statistics of variables for individual children (IFPRI2015 only)

Variables	2015 (sample = 1,514)	
	Mean	Std. dev
Child age (days)	810.74	507.74
Child gender (female = 1)	0.50	0.50
Caregiver's age (year)	29.71	9.06
Caregiver's education (year)	8.57	2.65
Birth quarter 1 (yes = 1)	0.23	0.42
Birth quarter 2 (yes = 1)	0.21	0.41
Birth quarter 3 (yes = 1)	0.30	0.46
Birth quarter 4 (yes = 1)	0.26	0.44
Birth order	3.45	2.31
Prebirth rainfall in 12 months before birth (millimeters)	247.13	80.65

Source: Authors.

Table 5. Balancing properties improved after the first stage probit (Share [%] of unbalanced variables)

Categories	ADS				APV			
	2015		2018		2015		2018	
	Raw	*IPW*	*Raw*	*IPW*	*Raw*	*IPW*	*Raw*	*IPW*
At 5% significance	43	2	56	0	49	0	50	0
At 10% significance	53	4	63	0	57	0	58	0
No. of observations	1,525		1,033		1,525		1,033	

Source: Authors.

Note: ADS = agricultural diversity score; APV = agricultural production values; IPW = inverse-probability weighted.

Table 6. Diagnostic statistics of generalized propensity score method

Categories	Low nighttime light area (2015)[a]	High nighttime light area (2015)[a]	Low nighttime light area (2018)[a]	High nighttime light area (2018)[a]
p-value (H_0: normality)	.582	.538	.579	.435
Share (%) of unbalanced variables				
At 5% significance	4	1	5	5
At 10% significance	10	4	8	8
No. of observations	801	724	599	434

Source: Authors.

[a]"Low nighttime light" and "High nighttime light" here refer to below- and above-median nighttime light intensity in the sample, respectively. Since nighttime light intensity is an integer value, median does not equally split the sample.

Table 7. Effects of the change in APP on the marginal effects of cooking time on nutritional outcomes, differentiated by nighttime light intensity and VCE (NGPS-IPW)

Nutritional outcome	APP	Year	Sub-sample by the level of nighttime light intensity and household's cooking-equipment value										
			Nighttime light – *Low*		Nighttime light – *High*		Cooking equipment value - *Low*		Cooking equipment value - *High*		All		
			(A)	(B)	(A)	(B)	(A)	(C)	(A)	(C)	(A)	(B)	(C)
Women's dietary diversity score	ADS	2015	1.248†	-.323*	.125	.233	-.126	-.108	-.107	.100	-.072	.033	.019
	APV	2015	-.099	-.173†	.007	.165	.103	-.165†	-.114	-.050	-.161	-.015	-.156*
	ADS	2018	.183	.166	-.319†	-.012	-.033	-.092*	-.157	.030	.076	.033	.055
	APV	2018	-.527*	-.219*	.255	-.053	-.369	-.086*	-.384†	-.002	-.246	-.122	-.006
Minimum dietary diversity score	ADS	2015	-.031	-.056*	.036	.057†	-.042	.007	-.027	.016	-.001	.022	.023
	APV	2015	-.028	-.004	.046	.036	.008	-.016	.006	.046†	-.026	.016	-.009
	ADS	2018	.078†	.015	-.022	-.037	.086†	-.006	-.054	.005	.038	.003	.003
	APV	2018	-.028	-.050†	.019	-.045	-.032	-.018*	-.056	-.007	-.032	-.032†	-.010
Children's minimum acceptable diet	ADS	2015	NA	NA	NA	NA	NA	NA	NA	NA	-.034	.096	-.112***
	APV	2015	NA	NA	NA	NA	NA	NA	NA	NA	-.047	-.090†	-.003
Children's minimum acceptable dietary diversity	ADS	2015	NA	NA	NA	NA	NA	NA	NA	NA	-.052	.026	-.100*
	APV	2015	NA	NA	NA	NA	NA	NA	NA	NA	-.060	-.074	-.011
Weight for age Z-score	ADS	2015	.016	-.095*	-.102*	.081*	-.022	-.231***	-.040	.003	-.031	.001	-.077*
	APV	2015	-.056	-.080*	.075	-.034	.029	-.098†	-.029	.064	.017	-.034	.025
Weight for height Z-score	ADS	2015	.001	-.088*	-.073	.085†	-.008	-.110†	-.048	-.002	-.032	-.006	-.058†
	APV	2015	-.057	-.044	.146**	.011	-.012	-.085†	.027	.039	.039	-.026	.006

Source: Authors.

Note: Symbols indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; NA = not available due to small sample size; NGPS-IPW = generalized-propensity-score-based inverse probability weighting method; VCE = value of cooking equipment.

(A) = average marginal effects of an increase in APP on the marginal effects of cooking time on nutritional outcomes.

(B) = effects of an increase in APP on the effects of cooking time interacted with cooking equipment value.

(C) = effects of an increase in APP on the effects of cooking time interacted with nighttime light intensity.

Table 8. Effects of the change in APP and cooking time on the intrahousehold inequality of nutritional outcomes among women and children, differentiated by nighttime light intensity and VCE (NGPS-IPW)

Nutritional outcome for which inequality among women and children is measured	APP	Year	Sub-sample by the level of nighttime light intensity and household's cooking-equipment value										
			Nighttime light – *Low*		Nighttime light – *High*		VCE - *Low*		VCE - *High*		All		
			(A)	(B)	(A)	(B)	(A)	(C)	(A)	(C)	(A)	(B)	(C)
Women's dietary diversity score	ADS	2015	.003	-.006	-.075	.009	.012	-.003	-.005	.005	-.013	.005	-.010
	APV	2015	.004	.087	.032	.050	.046	-.011	-.018	.005	.052	.012	.007
	ADS	2018	-.154†	-.091	-.034	-.083	.184	.092	-.084	.089	.004	.086†	.057
	APV	2018	.079	-.091	-.050	.071	.047	-.062	-.003	.117	.064	.047	-.009
Weight for age Z-score	ADS	2015	-.203	-.087	-.357*	-.066	-.003	-.019	-.085	.008	-.159†	-.044	-.012
	APV	2015	-.151	.003	-.260†	-.124	-.045	.065	-.147	.023†	-.085	.011	.025
Weight for height Z-score	ADS	2015	.083	-.293	-.082	.104	-.200	-.024	.278*	-.006	-.072	-.045	-.043†
	APV	2015	-.055	.097	-.418*	-.045	-.027	-.002	.012	-.018	-.034	.056	-.022

Source: Authors.

Note: Symbols indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; NGPS-IPW = generalized-propensity-score-based inverse probability weighting method; VCE = value of cooking equipment.

(A) = average marginal effects of an increase in APP on the marginal effects of cooking time.

(B) = effects of an increase in APP on the effects of cooking time interacted with cooking-equipment value.

(C) = effects of an increase in APP on the effects of cooking time interacted with nighttime light intensity.

Table 9. Effects of one standard deviation change in APP and cooking time on nutritional outcomes (IVGMM)

Nutritional outcome	APP	Year	Sub-sample by the level of nighttime light intensity and VCE			
			Nighttime light – *Low*		Nighttime light – *High*	
			VCE - *Low*	VCE - *High*	VCE - *Low*	VCE - *High*
Women's dietary diversity score	ADS	2015	.790**	-.050	-.910	-.194
	APV	2015	.634*	-.476	-.296	.050
	ADS	2018	-.361	-.378	-.254	-.043
	APV	2018	.970	-1.626*	.357	.616
Minimum dietary diversity score	ADS	2015	.068	-.204**	-.012	.077
	APV	2015	.577***	-.297**	-.163	-.004
	ADS	2018	-.037	-.050	-.101	-.045
	APV	2018	.246*	-.008	1.882	.564
Children's minimum acceptable diet	ADS	2015	-.001	-.001	-.117***	-.117***
	APV	2015	.121**	.121**	.187***	.187***
Children's minimum acceptable dietary diversity	ADS	2015	.072*	.072*	-.168***	-.168***
	APV	2015	.137**	.137**	.125***	.125***
Weight for age Z-score	ADS	2015	.114**	-.040	-.185***	-.039
	APV	2015	-.299	-.141	.077	-.086
Weight for height Z-score	ADS	2015	-.003	-.219***	-.104*	.032
	APV	2015	.526**	-.028	.216	-.408***

Source: Authors.
Note: Asterisks indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; IVGMM = instrumental-variable GMM; VCE = value of cooking equipment.

Table 10. Effects of one standard deviation change in APP and cooking time on the intrahousehold inequality of nutritional outcomes among women and children (IVGMM)

Nutritional outcome for which inequality among women and children are measured	APP	Year	Sub-sample by the level of nighttime light intensity	
			Nighttime light - *Low*	Nighttime light - *High*
Women's dietary diversity score	ADS	2015	-.346**	-.155
	APV	2015	-.924***	-.261
	ADS	2018	.356	.702*
	APV	2018	-.321	.406
Weight for age Z-score	ADS	2015	-.016	.208*
	APV	2015	-.247	-.527
Weight for height Z-score	ADS	2015	-.125	-.021
	APV	2015	.448	-.271

Source: Authors.

Note: Symbols indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; IVGMM = instrumental-variable GMM.

Table 11. Diagnostic tests of IVGMM for individual nutritional outcomes

Nutritional outcome	APP	Year	Sub-sample by the level of nighttime light intensity and VCE							
			Nighttime light – <u>Low</u>				Nighttime light – <u>High</u>			
			VCE - <u>Low</u>		VCE - <u>High</u>		VCE - <u>Low</u>		VCE - <u>High</u>	
			Under[a]	*Ortho*[a]	*Under*[a]	*Ortho*[a]	*Under*[a]	*Ortho*[a]	*Under*[a]	*Ortho*[a]
Women's dietary diversity score	ADS	2015	.000	.194	.000	.170	.000	.163	.000	.402
	APV	2015	.064	.132	.117	.155	.000	.132	.509	.149
	ADS	2018	.051	.420	.052	.190	.348	.297	.000	.301
	APV	2018	.128	.175	.026	.155	.137	.175	.254	.194
Minimum dietary diversity score	ADS	2015	.149	.145	.399	.521	.516	.148	.737	.662
	APV	2015	.000	.269	.000	.454	.000	.100	.294	.416
	ADS	2018	.051	.893	.108	.200	.806	.543	.235	.130
	APV	2018	.044	.855	.971	.382	.603	.236	.991	.140
children's minimum acceptable diet	ADS	2015	.055	.420	.055	.420	.000	.248	.000	.248
	APV	2015	.095	514	.095	514	.000	.211	.000	.211
children's minimum acceptable dietary diversity	ADS	2015	.093	.149	.093	.149	.006	.336	.006	.336
	APV	2015	.007	.370	.007	.370	.000	.159	.000	.159
weight-for-age Z-score	ADS	2015	.006	.797	.046	.269	.000	.279	.070	.159
	APV	2015	.179	.293	.006	.161	.034	.169	.230	.261
weight-for-height Z-score	ADS	2015	.001	.150	.145	.484	.062	.175	.127	.191
	APV	2015	.093	.219	.024	.268	.000	.156	.067	.709

Source: Authors.

Note: ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; IVGMM = instrumental-variable GMM; VCE = value of cooking equipment;

[a]*Under* = p-value for under-identification test (H_0: model is under-identified); *Ortho* = p-value for the violation of orthogonality condition (H_0: orthogonality holds and model is consistent).

Table 12. Diagnostic tests of IVGMM for intrahousehold inequality in nutritional outcomes

Nutritional outcome for which inequality among women and children are measured	APP	Year	Sub-sample by the level of nighttime light intensity			
			Nighttime light - Low		Nighttime light - High	
			Under[a]	*Ortho*[a]	*Under*[a]	*Ortho*[a]
women's dietary diversity score	ADS	2015	.000	.127	.000	.673
	APV	2015	.000	.159	.000	.673
	ADS	2018	.043	.162	.150	.732
	APV	2018	.000	.138	.550	.623
weight-for-age Z-score	ADS	2015	.159	.502	.017	.193
	APV	2015	.063	.152	.074	.172
weight-for-height Z-score	ADS	2015	.000	.282	.014	.284
	APV	2015	.024	.526	.000	.465

Source: Authors.

Note: ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; IVGMM = instrumental-variable GMM.

[a]*Under* = p-value for under-identification test (H_0: model is under-identified); *Ortho* = p-value for the violation of orthogonality condition (H_0: orthogonality holds and model is consistent).

Table 13. Effects of one standard deviation increase in technical efficiency on the effects of cooking time on nutritional outcomes

Nutritional outcomes	Year	Sub-sample by the level of nighttime light intensity and VCE			
		Nighttime light – _Low_	Nighttime light – _High_	VCE - _Low_	VCE - _High_
WDS	2018	.174*	-.045	.332***	.039
WDSM	2018	.025*	-.026	.037*	-.004
WDS inequality	2018	.008	-.014	.074	-.052

Source: Authors.

Note: Symbols indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. WDS = women's dietary diversity score, WDSM = minimum acceptable dietary diversity score, VCE = value of cooking equipment.

Table 14. Summary of interactive effects of APP and household cooking time on nutritional outcomes

Nutritional outcomes	APP / Characteristics	Average		Effect of reduced nighttime light		Effect of reduced VCE	
		IPW	IVGMM	IPW	IVGMM	IPW	IVGMM
Women's dietary diversity score	ADS	0	0	+	+	+	+
	APV	0	0	+	+	+	+
	TE	0	NA	+	NA	+	NA
Minimum dietary diversity score	ADS	0	0	0	0	0	0
	APV	0	0	0	+	0	+
	TE	0	NA	+ (?)	NA	+ (?)	NA
Children's minimum acceptable diet	ADS	0	0	+	+	0	0
	APV	0	+	0	0	0	0
Children's minimum acceptable dietary diversity	ADS	0	0	+	+	0	0
	APV	0	+	0	0	0	0
Weight for age Z-score	ADS	0	0	0	+	+	0
	APV	0	0	0	0	0	0
Weight for height Z-score	ADS	0	−	0	+	+	+, −
	APV	0	0	0	+	0	+

Source: Authors.

Note: ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; IPW = inverse probability weighted; IVGMM = instrumental-variable GMM; NA = not applicable; TE = technical efficiency; VCE = value of cooking equipment.
"+", "–", "0" indicate statistically significantly positive, statistically significantly negative, statistically insignificant, respectively.

Table 15. Summary of interactive effects of APP and household cooking time on the intrahousehold inequality of nutritional outcomes among women and children

Nutritional outcome for which inequality among women and children are measured	APP / characteristics	Average		Effect of reduced nighttime light		Effect of reduced VCE	
		IPW	IVGMM	IPW	IVGMM	IPW	IVGMM
Women's dietary diversity score	ADS	0	−	0	−	−	0
	APV	0	−	0	−	0	0
	TE	0	0	0	0	0	0
Weight for age Z-score	ADS	−	+	0	−	0	0
	APV	0	0	0	0	0	0
Weight for height Z-score	ADS	0	0	0	0	0	0
	APV	0	0	0	0	0	0

Source: Authors.

Note: ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values; IPW = inverse probability weighted; IVGMM = instrumental-variable GMM; TE = technical efficiency; VCE = value of cooking equipment.
"+", "–", "0" indicate statistically significantly positive, statistically significantly negative, statistically insignificant, respectively.

Appendix A: Generalized-propensity-score-based inverse probability weighting method

GPS is estimated in the following way (Hirano & Imbens 2004; Bia & Mattei 2008). [12] Each household $h = 1, \dots, H$ is associated with a set of potential outcomes $\Pi_h(T_h)$, which is conditional on treatment T_h (cooking time in our case). Each h is associated with observed covariates $Z_{h,i}$, cooking time $T_h \in [t_0, t_1]$ where t_0 and t_1 are the lower and upper bounds of treatment level.

The conditional density of T given the covariates Z, can be denoted as $r(T, Z) = f_{T|Z}(T|Z)$. Specific GPS, based on the observed T_h, Z_h can be denoted as $R_h = r(T_h, Z_h)$. It is assumed that, within strata with the same $r(T, Z)$, the probability that $T = T_h$ is independent of Z, which is another way of saying that T_h is independent of Z_h once conditional on R_h, so that the changes in outcomes can be attributed solely to T_h once conditional on R_h.

GPS is estimated in the following way. First, T_h or its particular transformation (such as Diewert transformation) $g(T_h)$ are regressed on X_h, through the maximum likelihood method with normally distributed disturbance term. This regression estimates $r(T, Z) = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[-\frac{1}{2\hat{\sigma}^2}\{g(T) - \zeta(\hat{\gamma}, Z)\}\right]$ in which $\zeta(\hat{\gamma}, Z)$ is a function of Z and parameters $\hat{\gamma}$. Given $r(T, Z)$, we compute $R_h = r(T_h, X_h)$ for each observation h.

Balancing-tests. Balancing tests for GPS methods are typically conducted by comparing GPS-adjusted means of Z_h across subgroups that are defined based on the range of T_h. A standard approach (Hirano & Imbens 2004; Kluve et al. 2007) is to split the sample into three subsamples $G_j (j = 1, 2, 3)$ based on the terciles of T_h, divide each subsample into five blocks $G_{jk} (k = 1, 2, 3, 4, 5)$ based on the quintiles of the $R(T^m_{h,j}, Z_h)$ evaluated at the median of T_h within the tercile j, and then calculate the *t*-statistics for the equality of means of Z_h's between blocks G_{jk} and $G_{\xi k} (\xi \neq j)$.

[12] The description in this section draws largely on Takeshima et al. (2017).

Appendix B: More results

Table 16. Factors associated with APP (probit)

Variables	APP			
	ADS		APV	
	Coef.	Std. err.	Coef.	Std. err.
Average age of working-age members	.004	(.008)	-.014*	(.008)
Share of females among working-age members	.361	(.492)	.195	(.491)
Household size (female above 61)	-.149	(.130)	.148	(.130)
Household size (female, 15-60)	-.049	(.075)	-.024	(.075)
Household size (female, 6-14)	.002	(.038)	-.035	(.038)
Household size (female below 6)	-.056	(.041)	.013	(.042)
Household size (male, above 61)	.050	(.112)	.370***	(.113)
Household size (male, 15-60)	.075	(.058)	.092*	(.058)
Household size (male, 6-14)	.065*	(.040)	-.034	(.040)
Household size (male below 6)	.039	(.041)	.036	(.042)
Average years of formal education of working-age members	.024	(.021)	.032	(.021)
Durable assets	.005	(.019)	.018	(.019)
Improved sanitation	.127	(.221)	-.124	(.222)
Finished floor	.139*	(.073)	.032	(.074)
Finished wall	-.086	(.111)	.038	(.112)
Improved water source	-.111	(.078)	.032	(.078)
Own cows	.637***	(.073)	.698***	(.073)
Altitude	-.001*	(.001)	.000	(.001)
Distance to the river	.005	(.004)	.005	(.004)
Groundwater depth	-.005*	(.002)	-.001	(.002)
Ruggedness	.001*	(.001)	.000	(.001)
Obtained credit	-.057	(.124)	-.002	(.124)
Share of perennial crop area	.475***	(.171)	.089	(.173)
Remittances received in a year	.014†	(.010)	.015	(.010)
Owned farm area	.222***	(.076)	.412***	(.084)
Number of productive trees owned	.182**	(.074)	-.128**	(.065)
Food price	.237	(.299)	-.309	(.304)
Own refrigerator, freezer	-.178**	(.081)	-.085	(.081)
Inoculation campaign	-.143	(.139)	.225†	(.141)
Nighttime light	.008	(.007)	.002	(.008)
Distance to nearest food market	.075**	(.032)	.075**	(.033)
Distance to the nearest state daycare	.000	(.005)	.008*	(.005)
Garbage collection	-.265†	(.167)	-.357**	(.166)
Centralized sewage system	-.091	(.227)	-.060	(.224)
Other female members (15-60) without caretaken children	-.015	(.058)	-.019	(.059)
Expenditure on non-member helpers	.000	(.003)	.001	(.003)
Whether owing tractors	-.191	(.195)	-.057	(.201)
Number of other types of agricultural equipment owned	.112**	(.045)	.086*	(.047)
Whether the community receive government extension visit	.148*	(.088)	-.044	(.088)
Value of cooking equipment	.018	(.021)	.013	(.021)
District dummies	Included		Included	
Constant	Included		Included	
Sample size	1,525		1,525	
p-value (H_0: jointly insignificant)	.000		.000	

Source: Authors.

Note: Symbols indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. ADS = agricultural diversity score; APP = agricultural production practices; APV = agricultural production values.

Table 17. Generalized-propensity-score estimation of cooking time

Variables	2015		2018	
	Coefficient	Standard errors	Coefficient	Standard errors
Average age of working-age members	-.002	(.003)	.001	(.004)
Share of females among working-age members	.099	(.165)	.039	(.203)
Household size (female above 61)	.061	(.053)	.000	(.000)
Household size (female, 15-60)	-.034	(.039)	-.161***	(.053)
Household size (female, 6-14)	.021	(.040)	.096*	(.059)
Household size (female below 6)	.008	(.042)	.119**	(.060)
Household size (male, above 61)	.021	(.045)	-.022	(.060)
Household size (male, 15-60)	.015	(.033)	.020	(.035)
Household size (male, 6-14)	.039	(.037)	-.012	(.043)
Household size (male below 6)	-.019	(.038)	-.016	(.045)
Average years of education of working-age members	-.002	(.010)	-.019	(.017)
Durable assets	-.004	(.005)	.008	(.010)
Improved sanitation	.081	(.058)	.020	(.078)
Finished floor	.028†	(.019)	.002	(.034)
Finished wall	-.042†	(.029)	.004	(.028)
Improved water source	-.038*	(.020)	.017	(.030)
Own cows	-.030†	(.019)	-.065**	(.031)
Altitude	.000	(.000)	.001	(.001)
Distance to the river	.002*	(.001)	-.002	(.002)
Groundwater depth	.000	(.001)	-.003*	(.002)
Ruggedness	.000	(.000)	.000	(.001)
Obtained credit	-.041	(.032)	-.020	(.033)
Share of perennial crop area	-.040	(.046)	.036	(.059)
Remittances received in a year	.003	(.003)	-.007†	(.005)
Owned farm area	.017	(.019)	-.023	(.028)
Number of productive trees owned	-.007	(.017)	-.003	(.012)
Food price	.071	(.082)	.000	(.000)
Own refrigerator, freezer	-.009	(.021)	-.071**	(.029)
Nighttime light	.002	(.002)	-.002	(.003)
Value of cooking equipment	-.003	(.011)	-.006	(.014)
Inoculation campaign	.030	(.038)		
Distance to the nearest state daycare	.001	(.001)		
Distance to nearest food market	.001	(.009)		
Distance to the nearest road			-.524	(.565)
Distance to the nearest railway			-.809	(.563)
Garbage collection	.071*	(.044)		
Centralized sewage system	.003	(.060)		
Other female members (15-60) without caretaken children	.005	(.017)	.216***	(.073)
Expenditure on non-member helpers	.001	(.001)		
SD of the age of all WRA	-.001	(.002)	.000	(.002)
SD of the education of all WRA	.005	(.008)	-.002	(.012)
Average age of all WRA	.002	(.002)	.004†	(.002)
Average education of all WRA	.004	(.007)	.021*	(.012)
PR's age	-.003**	(.002)	-.008***	(.003)
PR's education	-.004	(.004)	-.008	(.008)
Number of caretaken children by all WRA	.008	(.036)		
Number of caretaken boys by all WRA	.031	(.049)		
Number of pregnant women in the household	-.031	(.053)		
Number of lactating women in the household	-.127***	(.046)		
Other members older than PR (male)	.037	(.041)	-.003	(.057)
Other members older than PR (female)	-.026	(.045)	-.151**	(.066)
Other members younger than PR (male)	-.013	(.036)	-.006	(.039)

Other members younger than PR (female)	-.026	(.038)	-.092*	(.056)
Other members same-aged as PR (male)	.045	(.050)	.028	(.071)
Other members same-aged as PR (female)	-.055	(.102)	-.154	(.198)
Number of caretaken children by the PR	.020	(.029)		
Number of caretaken boys by the PR	-.021	(.038)		
Whether PR is pregnant	.018	(.066)		
Whether PR is lactating	.084*	(.047)		
Whether owing tractors	-.007	(.051)	-.002	(.097)
Number of other types of assets owned	.016	(.012)	-.034*	(.020)
Whether the community receives government extension	-.035†	(.023)	-.038	(.062)
Day of the week dummy	Included		Included	
District dummy	Included		Included	
Intercept	Included		Included	
Sample size	1,525		1,033	
Log-likelihood	-540.123		-516.140	
p-value: (H_0: Jointly insignificant)	.000		.000	

Source: Authors.

Note: Symbols indicate the statistical significance: *** 1%, ** 5%, * 10%, † 15%. PR = primary respondent of the household; SD = standard deviation; WRA = women of reproductive age.

Table 18. Full results for some of the main equations on the effects of crop diversification score on various nutritional outcomes estimated from IPW (statistically significant signs)

Variables	Women's dietary diversity score (2015)	Weight for age Z-score	Weight for height Z-score	Children's minimum acceptable diet (2015 / 2018 combined)	Children's minimum acceptable dietary diversity (2015 / 2018 combined)
Cooking time					
VCE					
Cooking time * VCE	−	−	−	−	−
Average age of working-age members			−		
Share of females among working-age members					
Household size (female above 61)					
Household size (female, 15-60)					
Household size (female, 6-14)					
Household size (female below 6)	+			+	
Household size (male, above 61)	−				
Household size (male, 15-60)				−	
Household size (male, 6-14)					
Household size (male below 6)					
Average years of formal education of working-age members	+				
Durable assets	+		−		
Improved sanitation			+		
Finished floor					
Finished wall					
Improved water source					
Own cows			+		+
Altitude					
Distance to the river					
Groundwater depth			+		
Ruggedness					
Obtained credit					
Share of perennial crop area	+	+			
Remittances received in a year					
Owned farm area	−			+	
Number of productive trees owned	−				
Food price		−			
Own refrigerator, freezer		−			
Garbage collection	−				
Centralized sewage system		−			
Nighttime light	+				
Distance to nearest food market					
Distance to the nearest state daycare					
Inoculation campaign		−			
Other female members (15-60) without caretaken children					
Expenditure on non-member helpers					
Average age of all WRA					
SD of the age of all WRA					
Average education of all WRA					

SD of the education of all WRA					
Number of caretaken children by all WRA					
Number of caretaken boys by all WRA					
Number of pregnant WRA					
Number of lactating WRA					
Whether owing tractors					
Number of other types of agricultural equipment owned					
Whether the community receives government extension visit	–				
Age of the woman					
Education of the woman					
Age order within the household					
Age order within the household (among females)					
Marital status – in consensual union					
Marital status – widow	+				
Marital status – divorced					
Marital status – separated					
Number of caretaken children by the woman					
Number of caretaken boys by the woman					
Pregnant					
Lactating					
Relation dummy	Included				
Child's age					
Child's gender				–	–
Birth order					
Prebirth rainfall in 12 months before birth (millimeters)					
Birth quarter 1 (yes = 2)				+	
Birth quarter 1 (yes = 3)				+	
Birth quarter 1 (yes = 4)				+	+
Caregiver's age					
Caregiver's education			+		
Age of children 6-59 months (average in the household)					
Age of children 6-59 months (SD in the household)		–	–		
Child's caregiver's age (average in the household)					
Child's caregiver's age (SD in the household)					
Child's caregiver's education (average in the household)					
Child's caregiver's education (SD in the household)					
Birth-quarters of children (# of different birth-quarters)					
Birth-quarters of children (average in the household)					
Share of girls among children 6-59 months in the household					
Day of the week dummy	Included	Included	Included	Included	Included
District dummy	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included
Sample size	1,792	822	822	565	565

Source: Authors.

Note: IPW = inverse probability weighted; VCE = value of cooking equipment; SD = standard deviation; WRA = women of reproductive age.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS

1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org