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IFPRI Discussion Paper 01770

November 2018

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Agriculture–Nutrition Linkages in Tajikistan: Evidence from Household Survey Data

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Abstract

In Tajikistan, the poorest country in the Central Asia region and one of the poorest in the world, food consumption patterns remain inadequate for a significant share of the population. Undernutrition and child stunting, among other outcomes, remain prevalent. At the same time, overnutrition and obesity are becoming increasingly serious. Using pooled cross-section datasets collected in 2007 and 2015 from farm households in Khatlon province (the major agricultural area in Tajikistan), we investigate how key agricultural production practices (APPs) (household-level production diversification, land productivity, and production scale) are associated with household-level and individual-level nutritional outcomes, including dietary diversity and children's and women's anthropometric outcomes. We find that, in rural Khatlon, these APPs are positively associated with various nutritional outcomes at the household level. Furthermore, applying the methodologies of Lee (1979), Maddala (1983), and Björklund and Moffitt (1987), we find that a different set of factors affects the unobserved returns and costs of these APPs, which are heterogeneous across households, and that, importantly, adoption of these APPs is partly driven by the expected returns. However, despite the positive gross returns, diversifying farm production or raising land productivity is costly among small and resource-poor farms. Improving their access to land and agricultural capital, as well as improving overall land productivity, with particular support to women, may be critical for enhancing their nutritional outcomes by exploiting agriculture's linkages to such outcomes.

Keywords: agriculture–nutrition linkage, dietary diversity, anthropometrics, market access, two-stage probit analysis, Tajikistan

Acknowledgments

We thank the participants of the Annual Eurasian Food Security Conference in Dushanbe, 2017, the Third Annual International Conference on Agriculture, Food Security, and Nutrition in Eurasia in Moscow, 2018, and the seminar participants at the Tajik Academy of Agricultural Sciences in September 2018 for providing useful feedback for the paper; and we thank the field staff from Zerkalo for the 2015 data collection. We also thank the United States Agency for International Development, the CGIAR Research Program on Policies, Institutions, and Markets, and the CGIAR Research Program on Agriculture for Nutrition and Health, 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. Background

Agriculture–nutrition linkages in developing countries have been increasingly investigated in the literature (for example, Jones 2017; Ruel, Quisumbing, and Balagamwala 2018). Underlying the agriculture–nutrition linkage are a number of development and economic issues. First, the linkage is a potential impact pathway of agricultural development on human capital development. In rural areas in developing countries, household agricultural production is an economic activity that uses the most basic household resources of land and labor, and it can play an important role in human capital development. Agricultural development may either generate a surplus that can be invested into other sectors (Mosher 1966; Johnston and Mellor 1961), including human capital development through nutritional improvements, or raise returns to and induce further investments in human capital (Foster and Rosenzweig 1996). The inseparability of production and consumption decisions by farm households (Singh, Squire, and Strauss 1986; Le 2010; LaFave and Thomas 2016), as a result of the market imperfections and high transaction costs that prevail in many rural areas in developing countries, potentially reinforces certain aspects of the agriculture–nutrition linkage at the household level. If market imperfections are mitigated through proximity to food markets, a household's production and consumption decisions become more separable, weakening the household-level agriculture–nutrition linkage (Hirvonen and Hoddinott 2017).

If the agriculture–nutrition linkage is in fact present in rural areas partly due to the aforementioned inseparability and the semi-subsistence nature of the farm households, the nutritional returns to and costs of particular agricultural production practices (APPs) become less observable because they are determined more by nonmarket features like the utility function and the shadow values of inputs. To the extent that these returns and costs are more heterogeneous across households than are market values of outputs and inputs, the nutritional returns to and costs of APPs also become heterogeneous across households. Furthermore, these unobserved returns and costs may be associated in different ways with a different set of factors. Understanding the associations of these unobserved, heterogeneous returns and costs with observable characteristics therefore becomes important in designing appropriate agricultural interventions toward improving nutritional outcomes.

In this paper, we provide some insights into the aforementioned issues by investigating agriculture–nutrition linkages in the Republic of Tajikistan. Tajikistan serves as a particularly important case to investigate such linkages. Tajikistan is the poorest country in the Central Asia region, and one of the poorest countries in the world. Although progress has been made, food consumption patterns remain inadequate for a significant share of its population. Undernutrition and child stunting, among others, remain prevalent. At the same time, overnutrition and obesity are also becoming increasingly serious. The agricultural sector still employs half of the country's workforce (World Bank 2018) and is characterized by a large number of smallholders engaged in traditional semi-subsistence farming. Unlike in low-income countries in other regions, however, Tajikistan is endowed with a relatively good irrigation infrastructure and good education levels, which it partly inherited from socialist systems in the Soviet era.[1] Furthermore, the rugged terrain, mountain ranges, deserts in neighboring regions, among other factors, still pose

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[1] According to the FAO (2018), total areas equipped for irrigation (740,000 hectares) account for more than 90 percent of the country's arable land. Similarly, the adult literacy rate had been 98 percent in 1989 and reached 100 percent in 2012 (World Bank 2018), while the average year of formal education among the population age 25 years or above has remained above 10 since 1990, similar to Malaysia or Singapore today, and much higher than developing Asia (Barro and Lee 2013).

significant barriers against full integration into regional and international food markets. The local agricultural development therefore holds great potential to be a key driver of nutritional improvements.[2]

Using two rounds of pooled cross-section datasets collected in 2007 and 2015 in Khatlon province, the largest agricultural region of Tajikistan, we provide insight into how key APPs (that is, household-level diversification, land productivity, and production scale) are associated with household-level and individual-level nutritional outcomes, including dietary diversity and anthropometric outcomes. In doing so, we contribute to the literature on agriculture–nutrition linkages and impact evaluation. The cost-effectiveness of various APPs for achieving nutritional outcome goals is becoming increasingly important, and yet the information on such costs has been much less studied compared to the benefits (Ruel, Quisumbing, and Balagamwala 2018). The recent literature on impact evaluation often focuses on gross gains and does not consider costs (Heckman 2010; Eisenhauer, Heckman, and Vytlacil 2015). Part of the challenge is that oftentimes the true costs of adopting particular production practices are unobservable, especially for smallholders in countries such as Tajikistan, where significant inputs, such as land, labor, and seed, are used without formal market transactions. Following Eisenhauer, Heckman, and Vytlacil (2015), we employ methodologies developed by Lee (1979), Maddala (1983), and Björklund and Moffitt (1987) (referred to as the LMB method hereafter) to partly address these issues and provide insights into factors that are associated with the costs for households to adopt key APPs.

The results suggest that household-level nutritional outcomes are often positively associated with various APPs, suggesting strong agriculture–nutrition linkages. Consistent with earlier literature (Hirvonen and Hoddinott 2017), the household-level agriculture–nutrition linkages are generally stronger in areas with poor access to food markets, although some links are strong in both poor-market-access and good-market-access areas. In the poor-access areas, the linkage seems to operate largely through own consumption of household-produced foods, rather than through agricultural incomes and market purchase of food. Furthermore, the potential nutritional returns to and costs of APPs are heterogeneous across households and are affected asymmetrically by a different set of factors. Importantly, higher expected returns from these APPs seem to induce their adoption more.

This paper contributes to a various strand of literature. First, it adds more evidence to the growing literature that investigates or reviews the linkages between a household's agricultural production practices and various nutritional outcomes at both household and individual levels (Kumar, Harris, and Rawat 2015; Malapit et al. 2015; Shively, Sununtnasuk, and Brown 2015; Hirvonen and Hoddinott 2017; Jones 2017; Ruel, Quisumbing, and Balagamwala 2018). In so doing, this paper also contributes to the literature on nutrition outcomes in Tajikistan, which had largely been limited to linkages with factors other than agriculture (e.g., Azzarri and Zezza 2011). Lastly, methodologically this paper extends the literature on impact evaluation, which investigates the (often-unobserved) costs, in addition to the returns, of adopting particular behaviors (Lee 1979; Maddala 1983; Björklund and Moffitt 1987; Heckman 2010; Eisenhauer, Heckman, and Vytlacil 2015), through an application to the case of agriculture-nutrition linkages.

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[2] At the macro level, domestic production has remained a significant source of food items, except wheat products, vegetable oils, and sugar and sweeteners (Appendix A). Achieving dietary diversity therefore continues to rely on domestic agricultural production.

This paper is structured as follows. Section 2 describes data and key descriptive statistics. Section 3 describes the empirical framework. Section 4 presents and discusses the results. Finally, section 5 concludes.

2. Data

This study uses two datasets from Tajikistan, namely the Tajikistan Living Standards Survey (TLSS) data collected in 2007 and a household survey conducted by IFPRI in the Feed the Future (FTF) zone of influence (ZOI) in Khatlon province in 2015 (FTFS). Our analysis combines the TLSS and FTFS, which together constitute pseudo-panel data. Such approach allows us to eliminate certain unobserved district- (called *raion* in Tajikistan) fixed-effects which can otherwise confound the effects of APPs on nutritional outcomes.

In the TLSS, a total of 4,860 households were selected through multiple-stage random sampling methods (World Bank 2008). In the first stage, 270 clusters were randomly selected, originally based on the 2000 census and the 2005 Multiple Indicator Cluster Survey by UNICEF. In each cluster, 18 households were then randomly selected, resulting in the total sample size of 4,860 (World Bank 2008). The samples are representative at the country level, total urban and rural areas, as well as each of five main administrative regions (*oblasts*) including Khatlon province.

The FTFS data were collected in 2015 as a part of an exercise evaluating the progress in various food-security-related indicators in the ZOI where USAID had been implementing FTF projects (IFPRI 2016). A total of 2,000 households were interviewed from 12 *raions* in Khatlon province, which constitute the ZOI. The FTFS data collection was conducted between February 21 and March 17 in 2015, using somewhat complex sampling methods. Approximately 1,300 households out of the 2,000 samples were households that were also interviewed in another survey conducted earlier in 2012/13 for different purposes than the focus of this study. These 1,300 households were selected through multiple-stage random sampling; at the first stage, 100 clusters were selected based on probability proportional to size sample in 12 districts, from the list of enumeration areas provided by the Tajikistan State Statistical Agency, based on the 2010 census (IFPRI 2016). Twenty households were then randomly sampled from each cluster. The remaining 700 households were selected through the same methodologies, but instead using household listing in 2015. The data from 2012/13 were not used in our analyses because they contained neither agricultural modules, nor some key information like remittances.

In addition, various agroecological variables have been constructed from various spatial data sources. Soil-related information is obtained from FAO et al. (2012). Historical averages of rainfall and temperature data are from NOAA (2018). Elevation, slope, and topography are obtained from the United States Geological Survey (USGS 1996), and a terrain ruggedness index is calculated following Riley, DeGloria, and Elliot (1999) using those topographic data. Euclidean distance to the nearest major river is calculated using the map of major rivers from Lehner, Verdin, and Jarvis (2006). Groundwater table depth is from Fan, Li, and Miguez-Macho (2013).

Figure 1 illustrates the locations of the FTF ZOI districts in Tajikistan.

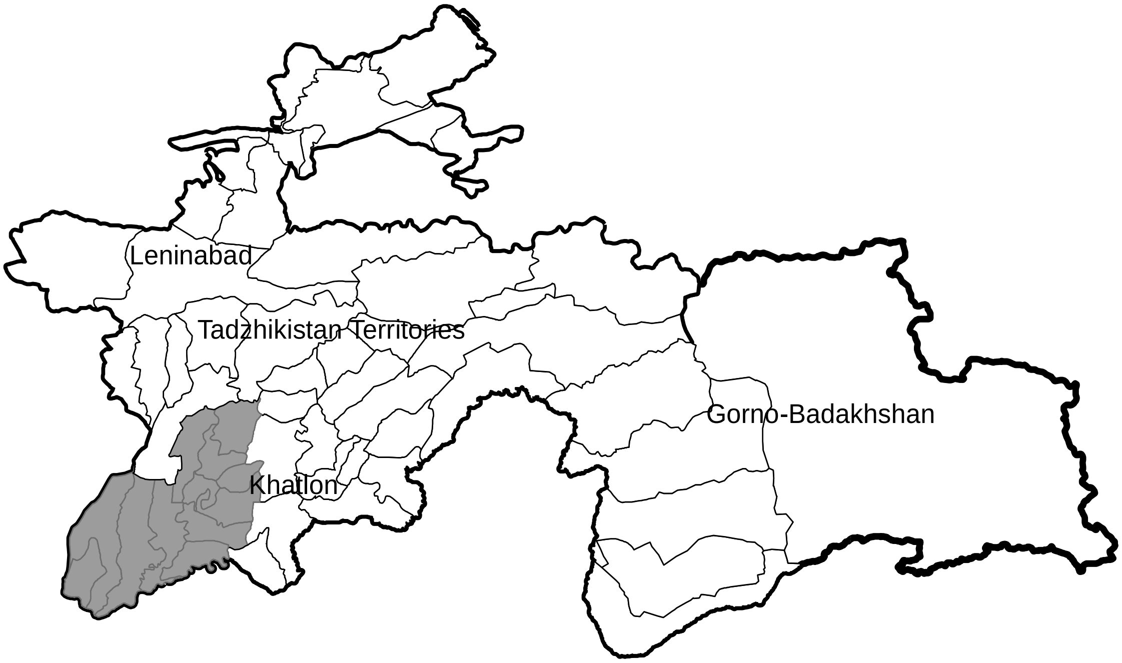

Figure 1. Districts in which data are analyzed (shaded area)
Source: Authors.

3. Empirical Framework

Our analyses focus on two aspects: (1) identifying associations between key household APPs/characteristics and nutritional outcomes; and (2) identifying factors associated with the heterogeneity of (unobserved) returns to and costs of these practices. Following the literature on nutrition-sensitive agriculture (Ruel, Quisumbing, and Balagamwala 2018) and based on the availability of information in our data (described in a later section), we focus on the following characteristics of household agricultural production: (a) production diversification measured by the number of food groups produced by the households (similar approaches were used by Kumar, Harris, and Rawat (2015) in Zambia and Malapit et al. (2015) in Nepal); (b) yield as was used in Shively, Sununtnasuk, and Brown (2015), but measured as gross production value per area cultivated; and (c) production scale measured as total production (Kumar, Harris, and Rawat 2015). As described below, the nutritional outcomes of our focus include the dietary diversity of households and individual women and children and anthropometrics of women and children.

3.1 Reduced-Form Model of the Associations between APPs and Nutritional Outcomes

This analysis is conducted using propensity score matching (PSM) and instrumental variables regression, both of which address the potential endogeneity of the aforementioned three key APPs. Propensity-score-based methods have been applied in various observational studies (not intervention-based studies) assessing the adoption impacts of agricultural technologies and practices (Takeshima and Nagarajan 2012; Mutuc, Rejesus, and Yorobe Jr. 2013; Takeshima 2017; Takeshima et al. 2017; including those in the nutrition-sensitive agriculture literature—Kabunga 2014). In PSM, while the agricultural production characteristics (a) through (c) are continuous variables, we construct binary variables that indicate above-median and below-median status, so that our empirical framework based on binary decision making can be applied.

Specifically, the following values are used as thresholds: (a) the number of food groups produced by the household is four or more; (b) the gross production value per hectare is 6,000 or above (in 2007 somoni); and (c) the gross production value per capita is 250 or above (in 2007 somoni).

Instrumental variables regression is estimated by the generalized method of moments (GMM), which is efficient in the presence of heteroskedasticity in idiosyncratic error terms (Hansen 1982). In GMM regression, the APPs are instrumented by two excluded variables, the size of own farm and the value of agricultural capital, which are expected to affect various nutritional outcomes only through the APPs, once other more liquid household asset variables are controlled for.[3] Both endogeneity and identification conditions are tested to make sure the estimates are efficient and consistent.

Specifically, PSM provides the estimated effects of the APPs on nutritional outcomes as average treatment effects on the treated (ATT):

$$ATT = E\left\{\frac{[T_i - p_i(X_i, Z_i, W_i)]Y_i}{1 - p_i(X_i, Z_i, W_i)}\right\}/P(T_i = 1), \tag{1}$$

where T_i is a binary variable taking the value of 1 for each APP if the values of the APPs (number of food groups produced, gross production value per hectare, gross production value per capita), denoted as S_i, exceed the aforementioned thresholds, and 0 otherwise. Y_i is the nutritional outcome of interest (such as the household dietary diversity score [HDDS], children's anthropometric outcomes, and so forth), X_i = exogenous variables that are expected to affect both the gross returns to and costs of APPs, W_i = exogenous variables that are expected to affect the costs (but not the returns), and Z_i = exogenous variables that affect the returns (but not the costs). $p_i(\cdot)$ is the propensity that $T_i = 1$ estimated as the function of all observable exogenous variables, while P is the unconditional probability that $T_i = 1$. Lastly, $E\{\cdot\}$ represents the expected values calculated from relevant samples.[4]

The GMM is estimated by selecting parameters β that minimize the moment condition, such that

$$\hat{\beta} = \arg\min_{\beta}[E(m_i)]'\widehat{\Omega}[E(m_i)] \tag{2}$$

$$m_i = (Y_i - X_i^{*}\beta)X_{i,IV}, \tag{3}$$

where $E(m_i)$ is the moment condition, $X_i^{*} = (X_i, Z_i, S_i)$, while $X_{i,IV} = (X_i, Z_i, W_i)$, and $\widehat{\Omega}$ is the suitable weighting matrix that is also estimated jointly with $\hat{\beta}$.

3.2 Structural Model of Gross Benefits and Costs

This analysis is conducted using structural models, as described below.

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[3] While the validity of these instrumental variables are ultimately an empirical question, as is shown in our results section, these instrumental variables are found to satisfy exclusion restrictions in our specifications.

[4] The PSM estimation results can be sensitive to the matching method used. We primarily use nearest-neighbor matching. The maximum number of neighbors is set at 4 rather than 1 since doing so leads to better large-sample properties (Abadie and Imbens 2002) and is often more efficient (Caliendo and Kopeinig 2008). To improve consistency, however, we also apply a caliper of 0.01 (meaning neighbors that are more than 0.01 propensity score apart are not matched), as doing so often improves the consistency of the estimates (Caliendo and Kopeinig 2008).

Framework

Our analytical framework follows the line of literature on LMB method, which has recently been revisited by Eisenhauer, Heckman, and Vytlacil (2015). Agent *i* (which can be either an individual or a household)[5] maximizes the utility $U(Y_i - \phi_i T)$. ϕ_i denotes the implicit costs of adopting the activity. As in Björklund and Moffitt (1987), it is assumed that ϕ_i captures costs in both monetary value and monetized utility. Gains from adopting particular APPs, α_i, are such that

$$U(Y_i^0 + \alpha_i - \phi_i) > U(Y_i^0), \tag{4}$$

where Y_i^0 represents the outcomes achieved without adopting the specific APPs. An important feature of this framework is that different factors can lead to heterogeneity in α_i and ϕ_i, respectively.

Modifying Björklund and Moffitt (1987), the underlying structural conditions can then be described as follows:

$$Y_i = X_i\gamma + Z_i\delta + \varepsilon_i + u_i \qquad \text{if } T_i = 1 \tag{5}$$
$$Y_i = X_i\gamma \qquad + \varepsilon_i \qquad \text{if } T_i = 0 \tag{6}$$
$$T_i = 1 \qquad \text{if } T_i^* > 0; \qquad T_i = 0 \text{ otherwise} \tag{7}$$
$$T_i^* = Z_i\delta - W_i\eta + u_i - v_i \tag{8}$$
$$\alpha_i = Z_i\delta + u_i \qquad (\alpha_i \text{ is unobserved}) \tag{9}$$
$$\phi_i = W_i\eta + v_i \qquad (\phi_i \text{ is unobserved}), \tag{10}$$

where T_i^* is a latent variable that determines T_i. X_i may perfectly overlap with Z_i. X_i may also overlap partly with W_i, but for the model to be identified, at least two variables that enter in X_i should not be in W_i. Parameters γ, δ, and η are corresponding coefficients. ε_i is an idiosyncratic error that affects the outcome Y_i regardless of T_i. u_i is an idiosyncratic error that affects the gross returns α_i, while v_i is an idiosyncratic error that affects the costs ϕ_i.

The empirical contribution of this method is that without the observed information on the gross returns α_i or the costs ϕ_i, we can estimate them as functions of exogenous variables Z_i and W_i. The model is particularly powerful in cases where there is no information on costs at all (Eisenhauer, Heckman, and Vytlacil 2015). In many cases, while outcomes such as HDDS or anthropometric conditions are partly observable (at least in the actual regime, even though counterfactual outcomes are unobservable), the returns to and costs of adopting particular APPs are not easily observable, partly because of the semi-subsistence nature of the farm households.

Estimation Methods

The parameters in (5) through (10) are estimated in the following way, which Lee (1979) called "two-stage probit analysis" (see Lee [1979] for the proof of the consistency of this estimate). These are estimated as multiple-step limited-information maximum likelihood, rather than as full-information maximum likelihood. While the latter is more efficient than the former, the former is often more robust because the earlier-stage regression estimates are unaffected by potential misspecifications in the later stages.

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[5] For now, we treat the household as the unit of aggregate decision making, as it is beyond the scope of this paper to analyze the intrahousehold dynamics of individual decision making.

First, we estimate

$$T_i = Probit(X_i, W_i) \tag{11}$$

and

$$Y_i = OLS_T(X_i, Z_i, \lambda_i), \tag{12}$$

in which λ_i is the inverse Mills ratio obtained from (11).[6] The equation (12) is estimated separately for samples with adopters ($T_i = 1$) and nonadopters ($T_i = 0$).

Using the predicted values based on (12), the gross benefits of adopting particular agricultural practices ($\Delta\hat{Y}_i$) are estimated as

$$\Delta\hat{Y}_i(X_i, Z_i, W_i) = \left(\hat{Y}_i\big|_{T_i=1} - \hat{Y}_i\big|_{T_i=0}; X_i, Z_i, W_i\right), \tag{13}$$

which is heterogeneous across agent i, and is associated with their characteristics X_i, Z_i, W_i.[7]

Following Lee (1979), Maddala (1983, section 8), and Björklund and Moffitt (1987), operationally, the cost equation $W_i\eta$ can be estimated by running the following regression:

$$T_i = Probit(X_i, W_i, \Delta\hat{Y}_i). \tag{14}$$

Because the estimated/predicted variables enter as exogenous variables, standard errors of estimates in (12) and (14) are computed by using 200 paired bootstraps (Efron 1979; Freedman 1981), which involves random resampling and repeating the whole estimation sequence above. Other studies have used a similar bootstrap method (Takeshima and Winter-Nelson 2012).

3.3 Variables

Nutritional Outcomes of Interest and Explanatory Variables

The nutritional outcome variables we are interested in include (1) HDDS, based on 7-day recall; (2) anthropometric figures (height-for-age, stunting) of children (0–59 months old), and body mass index (BMI) of women of reproductive age (15–49 years old); and (3) individual women's dietary diversity score (WDDS) and children's dietary diversity score (CDDS) (2015 only). These indicators are thought to capture important dimensions of nutritional outcomes, and they are commonly used in the nutrition-sensitive agriculture literature (Ruel, Quisumbing, and Balagamwala 2018).

Variables X_i

Household demographics include age and gender of household head, as well as number of male and female household members of various age groups (0–5, 6–15, 16–60, and 61 or above years old) (following Hirvonen and Hoddinott 2017). Past studies found greater effects of crop diversification on HDDS among female-headed households (Jones, Shrinivas, and Bezner-Kerr 2014). Human capital variables include the average years of completed formal education among working-age household members.[8]

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[6] As we describe below, some outcome variables are somewhat discrete (for example, HDDS, which takes only integer values). However, ordinary least squares has been applied commonly to ordinal discrete variables (Liu and Agresti 2005).

[7] Note that by including λ_i, (12)~~(12)~~ implicitly incorporates the cost of adopting the APPs, and thus models the variations in gross returns, not net returns. And, thus, the predicted variable $\Delta\hat{Y}_i$ is also the gross returns.

[8] We calculate years of completed formal education in the following way: = 4 if completing primary, = 9 if basic, = 11 if secondary general, secondary special, or secondary technical, = 15 if higher education or above.

Agroecological variables include elevation, historical rainfall, soil, hydrological conditions (proximity to the nearest major rivers, groundwater depth), and terrain ruggedness. Terrain ruggedness has been used increasingly in the literature as an indicator of isolation (Nunn and Puga 2012; Keefer and Khemani 2014; Takeshima 2017) and may be particularly relevant for Tajikistan given its geographic characteristics. In addition, the local area's share given to perennial crops is reported in 2015 data and is included for the 2015 sample to further control for certain local variations in farming systems.[9]

Wealth variables include the per capita value of durable assets owned by the household and the per capita value of agricultural equipment, as well as the ownership of cows, a key livestock animal. Access to finance is proxied by a variable indicating whether any household member has obtained credit from the formal sector. The amount of remittances received by households is included as well to capture the remittance income flows.

Key living conditions are also captured by the types of improved materials used for flooring and exterior walls, which are defined in IFPRI (2016, Table 3.3 footnote).[10] Sanitary and hygienic conditions are proxied by whether the household uses an improved source of drinking water[11] and an improved sanitation system.[12] We also include whether the community wherein the household resides has centralized garbage collection and disposal systems, as well as a centralized sewage system. An improved sanitation system is often considered an important factor affecting nutritional outcomes, particularly anthropometric outcomes (Mulmi et al. 2016).

Access to institutions is captured by the first principal components of the distance in kilometers to each type of nearest institution that is health related (hospital, polyclinic, feldsher point, first aid/ambulance, women's consultation, drugstore/pharmacy, doctor, children's doctor, and dentist), education related (state secondary school, private school, professional-technical school, institute/university), and food market related (state stores, private store, food market/bazaar, livestock market/bazaar, restaurant, café). Typically, these variables are closely correlated with each other. Consequently, the constructed first principal component captures around 70 percent of all the variations of respective variables.

For the child anthropometric model, additional variables are included in X that are not included in the household-level analysis. They include the age and gender of the child and ages as well as years of completed education of caregivers (often mothers). The birth quarter dummy is also included to capture seasonality effects of birth timing (Yamauchi 2012). Similarly, rainfall during the 12 months leading up to the birth of the child is included to account for the effect of prenatal environmental factors, as was studied in Shively, Sununtnasuk, and Brown (2015). Similarly, for the individual women's model, individual women's age, education level, and pregnancy status are included.

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[9] The perennial crop share is interacted with a 2015 year dummy variable, so that the value is 0 rather than missing values for the 2007 sample. This approach enables the estimation using both the 2007 and 2015 samples.

[10] Access to the electricity grid is almost universal among the sample households and is thus not included as a variable.

[11] In the Tajikistan Living Standards Survey (TLSS) in 2007, improved sources of drinking water include urban plumbing, rural plumbing, public tap/standpipe, hand pump, and protected dug well or spring; in the Feed the Future survey (FTFS) in Khatlon province in 2015, improved sources include piped water into the dwelling, piped water into the yard, a public tap/standpipe, a tube well/borehole, a protected dug well/protected spring, and rainwater, as classified by WHO and UNICEF (2006).

[12] 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 (TLSS and FTFS), and flush/pour flush to pit, composting toilet, ventilated improved pit latrine, and a pit latrine with a slab (FTFS) (WHO and UNICEF 2006).

For all the analyses, a year dummy variable is included to account for any potential variations in measurement across two surveys. Similarly, a dummy variable indicating the district included to account for any other remaining unobserved district-specific factors.

Variables Z_i and W_i

Variables Z_i include the ownership of a fridge, freezer, or microwave oven, which may affect a household's ability to store market-purchased food rather than growing it on its own. The composite price of food commodities in the community where the household resides is also included in Z, as higher prices may generally induce a household's agricultural production and the linkage with domestic production and nutritional outcomes. This variable is constructed as the average over all 12 food groups (used for the calculation of dietary diversity by FAO [2010]) reported in the local market.

Variables W_i include household farmland endowment (size of owned land) and agricultural capital endowment (value of agricultural capital owned). Such variables are likely to affect the costs of the various APPs (diversification, intensification, scale expansion), while they may not affect the benefits on nutritional outcomes once the effects of the resulting APPs are controlled for.

3.4 Descriptive Statistics

Table 1 provides descriptive statistics from the household-level data and Table 2 shows the statistics for individual children and women of reproductive age. Most of the sample consists of male-headed households, smallholders owning less than 1 hectare of farmland and modest agricultural capital. Although more than half of those own large livestock like cows, the share is lower in the 2015 data. Remittances account for a significant share of income. About half of the households have finished floors and improved sources of drinking water, but few households have improved sanitation or access to centralized garbage collection or sewage systems. The HDDS for the 2007 survey was somewhat higher than that for the 2015 survey, which was conducted during the lean season.[13]

[Insert Table 1]

Table 2 suggests that children in the area have particularly low height-for-age Z-scores and a high prevalence of stunting. Precipitation in the 12 months up to the month of birth and the caregiver's education level also vary to some extent. Some seasonality exists in the birth quarter, with July–September (April–June) having the highest (lowest) share of births. Dietary conditions of children remain inadequate, with only a fraction of children achieving a minimum acceptable diet and dietary diversity. Similarly, the share of women achieving a minimum acceptable level of dietary diversity is relatively low.

[Insert Table 2]

Table 3 shows the rough estimates of the share home-produced foods occupy in total household food consumption among the sample households. These figures are imputed using household-reported estimates of the consumption values. Overall, home-produced foods have

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[13] While the timing of the 2015 survey overlapped with the period for Navruz celebration, the survey revealed that consumption exclusively for Navruz accounted for a fairly small share of the overall consumption.

accounted for significant shares—close to 74 percent in the 2007 sample, which was collected during harvesting season, and 49 percent in 2015, which was collected during the lean season. Furthermore, the shares are slightly higher in areas with poor market access (57 percent) as opposed to 50 percent in areas with good market access. The considerably high share of home-produced food in total household food consumption suggests that household-level agriculture–nutrition linkages are strong, which motivates our analyses.

[Insert Table 3]

4. Results

We first discuss the associations between the three APPs and nutritional outcomes, based on PSM and GMM. We then discuss based on the LMB model how unobserved returns to and costs of the APPs may be associated with various factors.

4.1 Associations between APPs and Nutritional Outcomes

Table 4 and Table 5 summarize the estimated associations between various nutritional outcomes and three APPs—diversification in terms of the number of food groups grown (whether greater than four or not, for PSM), yield in terms of production value per hectare (whether 6,000 somoni per hectare [in 2007 somoni] or less, for PSM), and per capita production scale (whether 250 somoni per capita or more, for PSM)—estimated based on PSM and GMM. Specification test statistics show the consistency of the results; all models suggest that balancing properties are satisfied for PSM (Table 4). The PSM-related table shows Rubin's B score, whose values around 0.4 or less indicate satisfactory balancing property (Cochran and Rubin 1973; Rubin 2001). Rosenbaum (2002) or Mantel and Haenszel (1959) bounds are also shown, with values significantly greater than 1 suggesting the robustness of statistical significance against the violations of ignorability assumptions. Similarly, generally less than 10 percent of variables show statistically significant different means at 10 percent significance, which we would expect under the null hypothesis, so the samples are well balanced. The GMM results satisfy orthogonality conditions based on Hansen (1982)'s statistics, and sufficiently strong identification power based on Kleibergen and Paap (2006)'s under-identification tests.[14]

[Insert Table 4]
[Insert Table 5]

Overall, the results suggest that the three APPs are often significantly positively associated with various nutritional outcomes, including DDS (household and individuals) and individual anthropometrics. The results are generally consistent between the PSM and the GMM approaches, although the GMM results tend to exhibit a greater statistical significance.

In particular, the HDDS and WDDS measures are statistically significantly associated with all three APPs, based on both the PSM and GMM methods, suggesting that the agriculture–nutrition linkages are particularly strong for these outcomes. Household-level diversification in terms of the number of food groups grown seems to directly affect an aggregate dietary diversity of the household, and to reach individual female household members. These findings are consistent with those of several earlier studies (Ruel, Quisumbing, and Balagamwala 2018;

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[14] Because of the large number of regressions, the full results of the GMM and first-stage probit in PSM are not reported. However, they are available from the authors upon request.

Kumar, Harris, and Rawat 2015; Malapit et al. 2015). The results suggest that raising both diversity and yield or production scale may further complement each other, or that production systems are such that they are closely correlated with other.

Associations are also generally strong for diversification and scale expansion for children's height-for-age as well as the absence of stunting, more so than weight-for-age. This is consistent with the results of a study by Shively and Sununtnasuk (2015), who find that greater agricultural diversity or yield is negatively associated with stunting in Nepal. Effects on CDDS or diet acceptability are somewhat weaker under PSM, but they are statistically significantly positive when using GMM.

Associations of yield enhancement with nutritional outcomes are generally somewhat weaker. This may be due to the fact that most Tajik farm households are smallholders and thus a yield increase alone may have limited economic significance without significant production expansion or optimal diversification.

Associations with women's BMI are also generally weak for any of the APPs studied. Although this would suggest that the direct effects of agriculture on BMI may be limited, it also suggests that APPs can generally improve dietary diversity without worsening the double burden of nutrition, including, for example, overweight or obesity.

Differential Patterns by Access to Food Market

Table 6 summarizes the same set of results as in Table 4 and Table 5, but they are estimated using subsamples grouped based on the median value of the distance to the food market (measured as the first principal component) and their statistical significance. Importantly, many of the significant associations found for the whole samples are expected to be stronger in areas with poor access to food markets and to diminish in areas closer to the market. These patterns are particularly strong for both the WDDS and CDDS measures, as well as for children's height-for-age and stunting. This is because greater access to markets often enables households to specialize in production of commodities or activities other than the production of food crops, while using their incomes to purchase food commodities from the market. These findings are consistent with those of other studies (Hirvonen and Hoddinott 2017; Ruel, Quisumbing, and Balagamwala 2018). In good-access areas, some estimates are even significantly negative. This is potentially because in areas with good market access, including food markets, households may earn greater incomes from engaging in nonfarm activities, significantly raising the opportunity costs of either intensifying or expanding agricultural production. Again, these results are generally consistent between PSM and GMM.

[Insert Table 6]

Effects on Household Income

Table 4 and Table 5 suggest that the effects of the APPs on household income are somewhat weak, although they are statistically significantly positive for diversification and scale expansion in the GMM approach. As mentioned above, due to the nature of smallholders, enhancing yield alone may not significantly translate into household income, while diversification into higher-value crops or expanding scale may do so.

Similar to Table 6, Table 7 shows the differentiated results with respect to food market access. No clear difference is observed with respect to the effects of the APPs on household income. This may possibly be because, while the APPs in good-access areas may more readily translate into an agricultural income increase, because households' incomes may rely more on nonfarm sources, the effects on overall household incomes may be smaller. In contrast, the effects on income may be similarly limited in poor-access areas because of the difficulty in selling market surplus, even though agricultural income growth may more readily translate into greater household income.

[Insert Table 7]

At the least, the results suggest that the differential effects observed in Table 6 may not be because agriculture is more directly linked with household income in rural areas that tend to be more remote from food markets. Rather, the greater effects observed in poor-access areas may be more through the direct own home consumption of food produced by the households.

4.2 Associating Factors for Unobserved Returns and Costs of APPs

The analyses above provide only the average net effects of household APPs on nutritional outcomes. We provide further insight into the factors that give rise to the heterogeneity of gross returns and costs for adopting key production practices in terms of achieving nutrition outcomes. As described above, these gross returns and costs are unobservable for researchers, but we can still identify the factors contributing to them, using the aforementioned LMB method, which Eisenhauer, Heckman, and Vytlacil (2015) recently revisited.

Table 8 through Table 10 present the results for three key outcomes: HDDS, children's height-for-age, and WDDS. As we described in the methodology section, the signs of coefficients indicate their association with the unobserved returns to and costs of pursuing each of the three APPs, although the interpretation of the magnitudes of the coefficients is not straightforward.

[Insert Table 8]
[Insert Table 9]
[Insert Table 10]

Since the APPs are measured at the household level, only household-level variables are included in Table 8. In contrast, for the children's and women's equations (Table 9 and Table 10), individual-specific variables (such as age and gender of the respective individuals) are also included. This is mainly to maintain consistency, so that their association with returns from the APPs is more consistently estimated as they are more clearly separated from their effects on the costs of the APPs.

LMB models are run combining both good-access and poor-access samples, while including an access variable (distance to food market) as an explanatory variable. This is because, due to its complex nature, the LMB model has better large-sample properties than small-sample properties. However, as we describe below, the analysis still provides important insights that are generally applicable to both good- and poor-access areas.

In addition, in the LMB model, a significant loss of precision is observed due to multi-collinearity between the district dummies and other variables, including agroclimatic variables as well as distance to medical facilities, education facilities, and food markets. Therefore, district dummy variables as well as distances to medical/education facilities are excluded from the analysis. Including these variables generally led to similar signs but with a lower precision of estimated coefficients.

Key highlights of the results are the following. First, both returns to and costs of the APPs with respect to nutritional outcomes are significantly associated with various factors, indicating that these returns and costs are heterogeneous and vary across households or even individuals.

Second, oftentimes returns to and costs of particular APPs are associated with a different set of factors, or in different directions with the same factors. In an environment such as that of a developing country, where returns from APPs with respect to nutritional outcomes are generally high but costs also tend to be high, focusing on factors that are associated with lower costs may be more effective in promoting the agricultural sector's contribution to nutritional improvements. Of course, even in such an overall environment, some areas may actually suffer more from lower returns than high costs; for example, the costs of diversifying, intensifying, or scaling-up production may be relatively low due to lower labor costs, but the nutritional returns may be low. In such a case, focusing on factors that are positively associated with returns is more effective.

Certain factors are consistently associated with various APPs. Owning cows is generally associated with lower costs for diversification and production expansion, possibly because it allows easier diversification into the production of milk or meat or the use of greater draft power, though it is not significantly associated with the costs of yield enhancement or the returns from most APPs. Greater endowments of land and capital also generally lower costs, although owning more land actually raises the costs of yield enhancement (simply because it costs more to raise the yield for a larger farm). Higher average education of working-age members as well as greater remittances receipts also generally lower the costs of the APPs, which is largely consistent with earlier studies (for example, Azzarri and Zezza 2011) that found that child growth is positively associated with migration of household members.

Among agroclimatic conditions, greater rainfall is generally associated with higher returns and lower costs. Greater distance to the nearest river is also generally associated with lower costs of APPs. This may reflect the fact that in Tajikistan, proximity to a river may be less important given the fairly good irrigation systems built during the Soviet era, while prices of inputs may be higher in areas closer to the river due to the higher competition of agricultural production. A greater area share devoted to perennial crops is associated with lower costs of various APPs, potentially because once they have already grown, less maintenance is required than for field crops.

Costs of the APPs are generally negatively associated with greater distance to a food market. This is largely consistent with findings from the PSM and the GMM approaches—that is, poor access generally lowers the opportunity costs of APPs due to the lack of other nonfarm economic activities.

Owning a refrigerator or freezer is sometimes negatively associated with returns from APPs. This may be because such ownership can help the household store up a greater amount and diversity of food items purchased from the market, largely substituting for home production.

The associations with health- and hygiene-related factors are more ambiguous and depend on the nutritional outcomes investigated. However, some factors like improved housing conditions (finished walls) are negatively associated with returns from the APPs, indicating that these factors substitute for APPs in improving nutritional outcomes. Similarly, improved water sources or sewage systems are associated with higher costs of adopting the APPs. This suggests that improved water and hygiene facilities substitute for APPs, not by lowering the returns of

APPs but by potentially raising the opportunity costs of labor and other inputs, potentially because such improvements in water and hygiene facilities induce households to engage in economic activities other than farming.

Household demographics also have mixed but often significant effects on returns and costs, suggesting a complicated relationship including the tradeoff between short-term labor costs and longer-term human capital gains. Having a greater number of working-age female members relative to male members sometimes raises the costs of certain APPs although returns are also often higher, suggesting the importance of supporting such female members in the process of raising agricultural production efficiency. A greater number of adult males is also sometimes associated with lower returns from APPs, suggesting that it substitutes for APPs in nutritional improvements. In contrast, a greater number of adult females is often associated with higher returns from APPs. Given that their population is relatively declining due to emigration, as mentioned above, supporting female adult members is likely to be important through the effective support in APPs.

Third and lastly, the expected returns sometimes positively affect the adoption of APPs. This is particularly so between production expansion and children's height-for-age, and between diversification and WDDS. These patterns are consistent with the hypothesis that sufficiently high nutritional returns from APPs would induce households to recognize them and induce them to adopt the relevant APPs. These patterns are consistent with economic principles that say that sufficiently high returns can often induce agents to partly overcome market failures in information (nutrition knowledge) and capital (for adopting APPs).

5. Conclusions

Tajikistan lags behind neighboring Central Asian countries, including in nutritional outcomes like stunting. The Tajik population has enjoyed a relatively higher education level, partly as a legacy of the Soviet system, and growing remittance inflows have contributed to growth in income. In contrast, the agricultural sector is less developed, as the sector is still largely characterized by a large number of smallholders engaged in relatively traditional farming. The country's poor nutritional conditions may therefore be more closely linked to agriculture. Furthermore, rugged terrain and desert, among other things, still pose significant barriers against full integration into regional and international food markets, even though trade integration has been deepening over time. The relatively good irrigation infrastructure, combined with a high solar radiation endowment, among other factors, provides Tajikistan with significant potential for local production of a variety of food items and micronutrients, except certain grains, such as wheat, that have been increasingly imported. Tajikistan therefore serves as a useful case to investigate agriculture–nutrition linkages in a low-income country. We aimed to investigate such linkages by using two rounds of repeated cross-sectional data from Khatlon province, the major agricultural production area in Tajikistan.

In so doing, we also contribute to the literature on impact evaluation by applying the methodologies originally developed by Lee (1979), Maddala (1983), and Björklund and Moffitt (1987), and revisited by Eisenhauer, Heckman, and Vytlacil (2015). We focused on the fact that whereas the literature on the agriculture–nutrition linkage has provided rich insight into the impact of APPs on nutritional outcomes, few studies have investigated the heterogeneity in the returns to as well as the costs of such practices, and associated factors that explain part of such heterogeneity. This is partly because of the scarcity of information on actual returns and costs;

however, obtaining insight into factors associated with them is becoming increasingly important in designing nutrition and food security policies.

We find that in the study areas household-level crop diversification, land productivity, and production expansion are positively associated with various nutritional indicators at the household and individual levels, including dietary diversity and anthropometrics. In particular, the strongest effects are found on the HDDS and WDDS measures, children’s anthropometrics, and to some extent the CDDS metric. These effects are relatively stronger in poor-access areas and weaker in areas with better food market access. A substantial part of such effects in the poor-access areas may derive from own home consumption of home-produced foods. Furthermore, returns in the form of nutritional outcomes and costs of adopting particular APPs—such as diversification, yield enhancement, and scale expansion—are likely to be heterogeneous across households. Some factors affect only the returns or the costs, but some factors affect both returns and costs in the same direction, offsetting the potential gains. Improved sanitation, water and hygiene facilities, remittance incomes, and market access may substitute for household crop diversification, intensification, and expansion, but the role of agriculture remains important where these substitutions are insufficient. The results are also consistent with the view that supporting women in raising agricultural production efficiency and improving their access to land and agricultural capital (Mukhamedova and Wegerich 2018) remain critical in raising women’s and children’s nutritional outcomes through household agricultural production. Lastly, some results are consistent with the hypothesis that sufficiently high nutritional returns from agricultural practices could induce households to overcome various market failures that would otherwise constrain the adoption of such practices.

Table 1. Descriptive statistics (sample average)—household level

Variable	2007 sample	2015 sample	Whole sample
Household head age (year)	50.9	46.0	47.4
Female household head (yes = 1)	.140	.054	.078
Household size (male)			
0–5 years old	.439	.778	.684
6–15 years old	1.000	.872	.908
15–60 years old	2.33	1.88	2.21
61 and above years old	.184	.210	.202
Household size (female)			
0–5 years old	.415	.750	.659
6–15 years old	.896	.838	.854
15–60 years old	2.13	2.46	2.37
61 and above years old	.177	.201	.195
Average years of formal education of working-age members (years)	9.63	10.02	9.91
Durable assets per capita (2007 somoni)	6657.8	4436.2	5049.4
Own refrigerator, freezer (yes = 1)	.122	.316	.263
Own cow (yes = 1)	.745	.580	.625
Improved sanitation[a] (yes = 1)	.029	.029	.029
Finished floor[a] (yes = 1)	.572	.514	.530
Finished wall[a] (yes = 1)	.281	.132	.173
Improved water source[a] (yes = 1)	.278	.560	.482
In community with centralized garbage collection (yes = 1)	.011	.054	.042
In community with centralized sewage system (yes = 1)	.010	.033	.026
Distance to nearest food market—average of all types of markets (minutes)	30.7	24.7	26.3
Distance to nearest medical facilities—average of all types of facilities (minutes)	19.8	18.5	18.9
Distance to nearest education facilities—average of all types of facilities (minutes)	33.6	31.3	31.9
Obtained credit (yes = 1)	.013	.085	.065
Food price (average per kilogram of all 12 groups, 2007 somoni)	0.77	1.02	0.95
Altitude (meter)	542.6	413.8	449.8
Historical average annual rainfall (millimeters)	293.8	308.2	304.2
Euclidean distance to the river (geographical minutes)	.012	.015	.014
Groundwater depth (meters)	13.15	13.60	13.48
Terrain ruggedness index	33.16	51.06	46.12
Remittances received in a year (2007 somoni)	677.6	1914.4	1573.0
Owned farm area (hectares)	.191	.292	.264
Agricultural capital (2007 somoni)	24.7	116.9	91.5
Number of food groups produced by the household (out of 12 food groups)	4.40	3.15	3.49
Land productivity (gross production value in 2007 somoni/hectare)[b]	6005.1	6676.4	6428.6
Production scale (gross production value in 2007 somoni per capita)	412.7	671.5	600.1
Household dietary diversity score (count)	8.6	8.3	8.4

Source: Authors.

[a] See IFPRI (2016, Table 3.3 footnote) for definitions.

[b] Showing sample median, due to highly skewed distributions.

Table 2. Descriptive statistics at the individual level (children and women)

Variable	2007 sample	2015 sample	Whole sample
Children (6–59 months)			
Height-for-age Z-score	-1.44	-1.16	-1.23
Weight-for-age Z-score	-0.65	-0.63	-0.63
Weight-for-height Z-score	0.48	0.19	0.27
Stunting prevalence (yes = 1)	0.40	0.30	0.32
Age of the child (days)	1079.0	816.0	883.6
Gender of the child (female = 1)	0.49	0.49	0.49
Prebirth rainfall in 12 months before birth (mm)	502.2	629.4	597.7
Age of caregivers (year)	29.3	29.9	29.7
Education of caregivers (year)	9.9	6.2	8.1
Born in January–March (yes = 1)	0.27	0.23	0.24
Born in April–June (yes = 1)	0.21	0.21	0.21
Born in July–September (yes = 1)	0.30	0.29	0.29
Born in October–December (yes = 1)	0.22	0.25	0.26
Children (6–23 months)			
Meeting minimum acceptable diet[a] (yes = 1)	NA	0.06	0.06
Meeting minimum acceptable dietary diversity[a] (%)	NA	0.12	0.12
Women of reproductive age (15–49 years old)			
Dietary diversity score[a] (1-day recall)	NA	2.94	2.94
Dietary diversity score > 5 (yes = 1)	NA	0.24	0.24
Body mass index	NA	24.4	24.4
Age (year)	NA	29.2	29.2
Education (years completed)	NA	2.49	2.49
Pregnant (yes = 1)	NA	0.07	0.07

Source: Authors.

Note: NA = not available in the data.

[a] See IFPRI (2016, section 6) for definitions of these indicators.

Table 3. Share of home-produced food in total food consumption among sample farm households

Food group	Share (%) of own production		Imputed consumption value (2007 somoni/week)	
	2007	2015	2007	2015
Grains	84	41	65	67
Roots and tubers	33	17	6	4
Vitamin A rich veg. and other vegs	56	44	12	15
Vitamin A rich fruits and other fruits	73	49	6	5
Flesh meat	57	39	5	3
Egg	89	84	4	2
Fish and seafood	33	57	0.1	0.2
Legumes, nuts, and seeds	60	45	4	3
Milk and milk products	88	80	11	12
Oils and fats	39	11	5	5
Sweets	62	45	6	13
Spices, condiments, beverages	0	1	3	2
Total	74	49	124	132

Source: Authors.
Note: Exchange rate of somoni was approximately USD 1 = 3.5 somoni.

Table 4. Results of propensity score matching

Outcome	**Agricultural production practice**	**Coefficient (std. err.)**	**Rosenbaum (2002) or Mantel and Haenszel (1959) bounds**[a]	**No. observations**		**Balancing properties**	
				Adopters (on-support)	Nonadopters (on-support)	Rubin's B	% of variables with differences in means at 10% significance
Household dietary diversity score	Diversification	.372***(.081)	2.20	959 (942)	1120 (1120)	.251	3
	Yield	.249*** (.090)	1.65	825 (820)	807 (807)	.262	4
	Scale	.194** (.083)	1.60	1044(1021)	1035(1035)	.217	4
Children achieving minimum acceptable diet (yes = 1)	Diversification	-.011 (.032)		212 (178)	327 (327)	.514	7
	Yield	.005 (.029)		199 (172)	221 (221)	.529	0
	Scale	.016 (.028)		216 (168)	323 (323)	.408	0
Children achieving minimum acceptable dietary diversity (yes = 1)	Diversification	.045 (.041)		212 (178)	327 (327)	.514	4
	Yield	.047 (.040)		199 (172)	221 (221)	.529	0
	Scale	.038 (.038)		216 (168)	323 (323)	.408	0
Women's dietary diversity score	Diversification	.678*** (.108)	2.00	948 (939)	1483 (1483)	.286	8
	Yield	.388*** (.107)	1.55	992 (962)	958 (958)	.276	3
	Scale	.291** (.106)	1.45	1083(1045)	1348 (1348)	.242	3
Women achieving dietary diversity ≥ 5	Diversification	.134*** (.025)	1.70	948 (939)	1483 (1483)	.286	8
	Yield	.066*** (.025)	1.35	992 (962)	958 (958)	.276	3
	Scale	.024 (.025)		1083 (1045)	1348 (1348)	.242	3
Body mass index is normal	Diversification	-.026 (.028)		851 (832)	1339 (1339)	.261	0
	Yield	-.018 (.029)		886 (851)	867 (867)	.266	3
	Scale	-.001 (.029)		987 (952)	1203 (1203)	.288	7
Height-for-age (Z-score)	Diversification	.430** (.195)	1.75	352 (308)	546 (546)	.480	5
	Yield	-.094 (.214)		368 (307)	350 (350)	.529	10
	Scale	-.010 (.205)		452 (406)	446 (446)	.543	8
Not stunted (no stunting = 1)	Diversification	.112** (.051)	2.00	352 (308)	546 (546)	.480	3
	Yield	.002 (.055)		368 (307)	350 (350)	.529	4
	Scale	.089* (.049)	1.75	452 (406)	446 (446)	.543	10
Household income	Diversification	-.003 (.046)		959 (942)	1120 (1120)	.251	0
	Yield	-.032 (.049)		825 (820)	807 (807)	.262	4
	Scale	.004 (.045)		1044 (1021)	1035 (1035)	.217	3

Source: Authors.

[a] Rosenbaum (2002) bounds for continuous outcomes and Mantel and Haenszel (1959) bounds for binary outcomes (stunting), as suggested by Aakvik (2001).

Asterisks indicate the statistical significance:†15%, *10%, **5%, ***1%.

Table 5. Results of instrumental variables estimation (generalized method of moments)

Outcome	**Agricultural production practice**	**Coefficient (std. err.)**	**Sample size**	**p-values for respective null hypothesis**		
				No endogeneity[a]	Not overidentified[b]	Under-identified[c]
Household dietary diversity score	Diversification	.696** (.276)	2079	.048	.597	.002
	Yield	.097*** (.026)	1611	.602		
	Scale	.568** (.248)	2079	.069	.198	.012
Children achieving minimum acceptable diet (yes = 1)	Diversification	.002 (.007)	539	.416		
	Yield	.009 (.009)	414	.170		
	Scale	-.007 (.009)	539	.388		
Children achieving minimum acceptable dietary diversity (yes = 1)	Diversification	.018* (.010)	539	.181		
	Yield	.023* (.012)	414	.239		
	Scale	.001 (.012)	539	.150		
Women's dietary diversity score	Diversification	.258*** (.029)	2431	.718		
	Yield	.503*** (.168)	1924	.048	.764	.000
	Scale	.065** (.029)	2431	.276		
Women achieving dietary diversity ≥ 5	Diversification	.046*** (.006)	2431	.909		
	Yield	.135*** (.042)	1924	.016	.798	.000
	Scale	.000 (.007)	2431	.343		
Body mass index is normal	Diversification	.002 (.007)	2190	.727		
	Yield	-.018** (.008)	1724	.699		
	Scale	-.010 (.008)	2190	.337		
Height-for-age (Z-score)	Diversification	.120*** (.039)	898	.675		
	Yield	.005 (.063)	713	.196		
	Scale	.094* (.056)	898	.574		
Not stunted (no stunting = 1)	Diversification	.030***(.010)	898	.664		
	Yield	.012 (.016)	713	.386		
	Scale	.037*** (.014)	898	.709		
Household income	Diversification	.023** (.010)	2079	.315		
	Yield	.012 (.013)	1611	.836		
	Scale	.034*** (.013)	2079	.618		

Source: Authors.

[a] Based on Hausman's test. [b] Based on Hansen (1982)'s test. [c] Based on Kleibergen and Paap (2006).

Asterisks indicate the statistical significance:†15%, *10%, **5%, ***1%.

Table 6. Results differentiated by access to food markets

Outcome	Ag production practices[a]	Propensity score matching (PSM)			Instrumental variable regression		
		All	Poor access	Good access	All	Poor access	Good access
Household dietary diversity score	Diversification	.372***	.411***	.265**	.696**	.164***	.749**
	Yield	.249***	.176	.220*	.097***	.081*	.104***
	Scale	.194**	.302***	.104	.568**	.156***	.101***
Children achieving minimum acceptable diet (yes = 1)	Diversification	-.011	NA	.042	.002	.007	-.007
	Yield	-.005	NA	-.026	.009	.011	.014
	Scale	.038	NA	-.010	-.007	-.003	-.019†
Children achieving minimum acceptable dietary diversity (yes = 1)	Diversification	.045	NA	.055	.019*	.035***	-.007
	Yield	.047	NA	.029	.023*	.016	.040***
	Scale	.038	NA	.007	.001	.005	-.017
Women's dietary diversity score	Diversification	.678***	.796***	.595***	.258***	.306***	.200***
	Yield	.388***	.474***	.508***	.503***	.490***	.182**
	Scale	.291**	.280†	.160	.065**	.077*	.029
Women achieving dietary diversity ≥ 5	Diversification	.134***	.163***	.105***	.046***	.059***	.028***
	Yield	.066***	.085**	.092**	.135***	.148***	.034***
	Scale	.024	.037	-.015	.000	.009	-.011
Body mass index is normal	Diversification	-.026	-.035	.037	.001	-.012	.020**
	Yield	-.018	-.040	-.013	-.018**	.001	-.036***
	Scale	-.001	-.013	-.068*	-.010	.002	-.012
Height-for-age (Z-score)	Diversification	.430**	.286	.358	.120***	.143***	.071
	Yield	-.094	.148	-.568*	.005	.070	-.040
	Scale	-.010	.669**	-.515*	.094*	.243***	-.107
Not stunted (no stunting = 1)	Diversification	.112**	.026	.117†	.030***	.024*	.019
	Yield	.002	-.066	-.055	.012	.011	.005
	Scale	.089*	.191**	-.062	.037***	.048**	-.009

Source: Authors.

Note: NA = not available in the data. Shared cells indicate statistically significantly negative effects.

[a] Diversification for PSM: = 1 if number of crop groups ≥ 5, = 0 otherwise.
Yield for PSM: = 1 if greater than 6,000 somoni/hectare (in 2007 somoni), = 0 otherwise.
Scale for PSM: = 1 if per capita output > 250 somoni (in 2007 somoni), = 0 otherwise.

Table 7. Results differentiated by access to food markets (household income)

Outcome	**Ag production practices**	**Instrumental variable regression**			**Propensity score matching**		
		All	Poor access	Good access	All	Poor access	Good access
Income	Diversification	.023**	.012	.031**	-.003	.000	.001
	Yield	.013	.010	.017	-.032	-.001	.016
	Scale	.033***	.041**	.030*	.004	.092†	-.059

Source: Authors.

Asterisks indicate the statistical significance: †15%, *10%, **5%, ***1%.

Table 8. Decomposition of unobserved benefits and costs estimated by LMB method (household dietary diversity score)

Agricultural production practice	**Crop diversification**				**Land productivity**				**Production scale**			
Factors associated with returns or costs	**Returns**		**Costs**		**Returns**		**Costs**		**Returns**		**Costs**	
Age of household head	.002	(.005)	-.002	(.003)	-.002	(.007)	.001	(.012)	.003	(.005)	-.001	(.009)
Gender of household head	.493**	(.212)	.239	(.177)	.023	(.252)	-.172	(.292)	.360	(.260)	-.282	(.261)
Female, > 60 years old	.187	(.162)	-.139*	(.083)	.091	(.161)	-.070	(.279)	.121	(.166)	.121	(.296)
Female, 16–60 years old	.071	(.056)	.021	(.028)	.011	(.059)	.006	(.077)	-.002	(.065)	.108**	(.050)
Female, 6–15 years old	.084	(.065)	.010	(.041)	-.022	(.062)	.004	(.052)	.026	(.070)	.129**	(.064)
Female, < 6 years old	-.008	(.068)	.010	(.031)	.058	(.070)	.010	(.111)	.089	(.065)	.105	(.140)
Male, > 60 years old	-.045	(.174)	-.082	(.091)	-.098	(.177)	-.232	(.253)	-.275*	(.149)	-.248	(.689)
Male, 16–60 years old	-.018	(.061)	-.034	(.031)	-.129*	(.075)	-.085	(.195)	-.032	(.057)	.029	(.114)
Male, 6–15 years old	-.015	(.065)	.004	(.041)	.005	(.056)	.010	(.095)	-.025	(.072)	.125†	(.083)
Male, < 6 years old	.045	(.073)	-.016	(.038)	.184***	(.064)	.028	(.209)	.000	(.066)	.046	(.047)
Education	-.018	(.038)	-.040**	(.019)	-.025	(.039)	-.026	(.041)	-.043	(.037)	-.068	(.047)
Durable asset (ln)	.047†	(.032)	-.004	(.016)	.044	(.034)	-.008	(.042)	.068**	(.032)	-.009	(.110)
Improved sanitation	-.614*	(.326)	.128	(.255)	-.313	(.397)	-.062	(.628)	-.516†	(.340)	.119	(1.165)
Finished floor	-.114	(.128)	-.163*	(.090)	-.122	(.140)	-.048	(.317)	-.054	(.140)	.066	(.223)
Finished wall	-.043	(.189)	.025	(.088)	-.068	(.193)	-.158	(.232)	.091	(.166)	.077	(.185)
Improved water source	.156†	(.106)	.138*	(.071)	.136	(.139)	.058	(.250)	-.192*	(.112)	-.038	(.517)
Garbage collection	-.470*	(.275)	.291†	(.193)	-.658**	(.302)	.134	(.962)	.089	(.287)	.486	(.390)
Sewage system	.133	(.349)	.173	(.219)	.113	(.388)	.296	(.393)	.124	(.343)	.334	(.297)
Own cow	.349	(.265)	-.506***	(.095)	-.004	(.135)	-.114	(.118)	.097	(.191)	-.605***	(.175)
Distance to food market	.057	(.042)	-.071***	(.023)	.013	(.034)	-.021	(.043)	.028	(.034)	-.022	(.031)
Altitude	.000	(.000)	.000**	(.000)	.000	(.000)	.001*	(.000)	.000	(.000)	.000	(.000)
Rainfall	.001	(.002)	-.002*	(.001)	-.001	(.002)	-.002	(.003)	.000	(.002)	.000	(.003)
Distance to river	-.050	(.007)	-.130***	(.045)	.044	(.087)	-.158*	(.081)	.023	(.067)	-.104	(.099)
Groundwater depth	.000	(.005)	.010***	(.003)	.010**	(.004)	.000	(.010)	.002	(.003)	.003	(.004)
Ruggedness	-.001	(.001)	.000	(.001)	-.002	(.001)	.002	(.003)	-.002†	(.001)	.001	(.002)
Obtained credit	.071	(.252)	.052	(.140)	.053	(.307)	-.146	(.505)	.195	(.279)	-.010	(.602)
Area share of perennial crops (ln)	.149	(.290)	-.437***	(.143)	-.200	(.194)	-.285	(.426)	-.063	(.173)	-.126	(.205)
Remittances received (ln)	-.019	(.018)	-.014	(.010)	.035*	(.019)	.003	(.042)	.009	(.016)	-.025	(.049)
Food price	.456†	(.314)			.023	(.476)			.017	(.319)		
Own refrigerator, freezer	-.318**	(.137)			-.296*	(.159)			-.142	(.145)		
Inverse Mills ratio	-.630	(.696)			.296	(.545)			-.098	(.406)		
Owned farm area (ln)			-.278***	(.071)			.960***	(.175)			-.637***	(.166)
Agricultural capital (ln)			-.028*	(.015)			-.023	(.017)			-.014	(.015)
Year dummy	Included		Included		Included		Included					
Intercept	Included		Included		Included		Included		Included		Included	
Effects of expected benefit on the adoption	-.121 (.211)				.202 (1.229)				.186 (1.420)			
No. of obs.	2079		2079		1632		1632		2079		2079	

Source: Authors. Asterisks indicate the statistical significance: †15%, *10%, **5%, ***1%

Note: For this table as well as Table 9 and Table 10, standard errors are estimated through 200 paired bootstraps. “(ln)” indicates that variables are transformed in natural-log, due to high skewness. LMB = Lee (1979), Maddala (1983), and Björklund and Moffitt (1987).

Table 9. Decomposition of unobserved benefits and costs estimated by LMB method (height-for-age)

Agricultural production practice	**Crop diversification**				**Land productivity**				**Production scale**			
Factors associated with returns or costs	**Returns**		**Costs**		**Returns**		**Costs**		**Returns**		**Costs**	
Age of household head	.001	(.013)	.002	(.005)	-.008	(.015)	.003	(.005)	.000	(.011)	-.003	(.004)
Gender of household head	-.705	(.764)	.503**	(.238)	-1.379†	(.923)	-.029	(.265)	-.200	(.712)	-.169	(.205)
Female, > 60 years old	-.300	(.506)	-.414***	(.130)	.013	(.478)	-.063	(.120)	-.502	(.413)	-.194	(.140)
Female, 16–60 years old	.218	(.162)	-.082	(.062)	.095	(.181)	-.061	(.056)	.172	(.161)	.073	(.054)
Female, 6–15 years old	.228	(.171)	-.025	(.064)	.029	(.187)	-.009	(.047)	.184	(.189)	.123**	(.059)
Female, < 6 years old	-.008	(.185)	.014	(.050)	.080	(.204)	-.016	(.052)	-.346*	(.183)	.084†	(.054)
Male, > 60 years old	-.388	(.466)	-.257*	(.155)	-.014	(.529)	-.262*	(.141)	-.056	(.393)	-.195†	(.125)
Male, 16–60 years old	-.031	(.166)	-.096**	(.047)	-.202	(.206)	-.041	(.054)	-.343**	(.166)	.011	(.061)
Male, 6–15 years old	-.374**	(.158)	.055	(.073)	-.225	(.211)	.024	(.063)	.015	(.168)	.074†	(.049)
Male, < 6 years old	.126	(.163)	.008	(.054)	.195	(.196)	.070	(.050)	.180	(.164)	.085*	(.048)
Education	-.124	(.108)	-.038	(.042)	.017	(.127)	-.025	(.031)	.077	(.100)	-.036	(.029)
Durable asset (ln)	.049	(.074)	.040†	(.025)	.038	(.101)	-.019	(.028)	.076	(.085)	.009	(.025)
Improved sanitation	1.026	(.725)	.024	(.378)	-1.259	(1.148)	.161	(.427)	-.810	(.962)	-.277	(.273)
Finished floor	.211	(.301)	.088	(.111)	.134	(.396)	-.237**	(.101)	.645**	(.265)	.146†	(.098)
Finished wall	-.119	(.425)	-.315**	(.145)	-.845†	(.546)	-.260†	(.168)	-.583	(.416)	-.174	(.154)
Improved water source	.381	(.441)	.067	(.141)	-.139	(.442)	.297***	(.111)	-.261	(.422)	.095	(.117)
Garbage collection	-.960	(.967)	.095	(.350)	.334	(.966)	-.366	(.349)	.136	(.823)	.084	(.257)
Sewage system	-.490	(1.214)	1.010**	(.500)	.878	(1.164)	1.622**	(.794)	-.829	(1.073)	.258	(.358)
Own cow	-.604	(.721)	-.663***	(.153)	.230	(.376)	-.273**	(.111)	.287	(.541)	-.554***	(.124)
Distance to food market	-.002	(.145)	-.105***	(.040)	.142	(.111)	.045	(.034)	.008	(.091)	-.010	(.029)
Altitude	-.002**	(.001)	.000	(.000)	-.001	(.001)	-.000	(.000)	.001	(.001)	.000†	(.000)
Rainfall	.007	(.010)	-.007***	(.002)	-.018	(.012)	-.004**	(.002)	.005	(.007)	.000	(.002)
Distance to river	-.350*	(.212)	-.193***	(.070)	-.203	(.257)	-.180***	(.070)	-.077	(.211)	-.260***	(.053)
Groundwater depth	-.007	(.013)	.009**	(.004)	-.018†	(.012)	.001	(.004)	-.010	(.011)	.008**	(.004)
Ruggedness	.003	(.005)	.003†	(.002)	.003	(.007)	.005***	(.002)	.000	(.003)	.001	(.001)
Obtained credit	1.601	(1.166)	.042	(.368)	-.709	(1.076)	-.223	(.259)	.523	(.818)	-.102	(.250)
Area share of perennial crops (ln)	.192	(.825)	-.447**	(.233)	-.652	(1.039)	-.204	(.274)	.742	(.838)	.138	(.202)
Remittances received (ln)	-.006	(.054)	-.006	(.018)	-.017	(.049)	.016	(.015)	-.028	(.045)	-.039**	(.015)
Prebirth rainfall	-.166	(.869)			-.421	(1.108)			-.002	(.004)		
Born in April–June	-.094	(.397)			.199	(.539)			.185	(.544)		
Born in July–September	-.005	(.004)			.005	(.006)			.296	(.461)		
Born in October–December	-.375	(.471)			.671	(.489)			.466	(.481)		
Age of caregivers	-.162	(.479)			.473	(.417)			-.131	(.730)		
Education of caregivers	-.416	(.427)			.862*	(.458)			-.134*	(.075)		
Gender of the child	.630	(.746)			.476	(.830)			.486	(.387)		
Age of the child	-.041	(.079)			-.071	(.086)			.000	(.000)		
Food price	-.233	(.449)			.712†	(.463)			-2.392***	(.917)		
Own refrigerator, freezer	.000	(.000)			.000	(.000)			-.522	(.408)		
Inverse Mills ratio	.792	(1.368)			.248	(1.358)			-.476	(1.168)		
Owned farm area (ln)			-.429***	(.130)			-.667***	(.254)			-.750***	(.217)
Agricultural capital (ln)			-.007	(.023)			.043*	(.023)			-.045**	(.020)

Agricultural production practice	Crop diversification		Land productivity		Production scale	
Factors associated with returns or costs	**Returns**	**Costs**	**Returns**	**Costs**	**Returns**	**Costs**
Year dummy	Included	Included	Included	Included		
Intercept	Included	Included	Included	Included	Included	Included
Effects of expected benefit on the adoption	.059 (.152)		.083 (.116)		.205* (.110)	
No. of obs.	1055	1055	845	845	1055	1055

Source: Authors.

Note: LMB = Lee (1979), Maddala (1983), and Björklund and Moffitt (1987).

Asterisks indicate the statistical significance: †15%, *10%, **5%, ***1%.

Table 10. Decomposition of unobserved benefits and costs estimated by LMB method (women's dietary diversity score)

Agricultural production practice	**Crop diversification**				**Land productivity**				**Production scale**			
Factors associated with returns or costs	**Returns**		**Costs**		**Returns**		**Costs**		**Returns**		**Costs**	
Age of household head	.006	(.007)	.002	(.003)	.003	(.007)	-.001	(.004)	-.003	(.007)	.000	(.003)
Gender of household head	.821	(.585)	.916***	(.285)	-.587	(.422)	-.191	(.213)	.490	(.390)	-.329†	(.206)
Female, > 60 years old	-.081	(.199)	-.109	(.082)	.146	(.193)	-.015	(.097)	.115	(.198)	.075	(.086)
Female, 16–60 years old	.132*	(.079)	.047	(.040)	.353***	(.080)	-.083	(.086)	-.033	(.098)	.121***	(.030)
Female, 6–15 years old	-.111	(.088)	-.067†	(.042)	.199**	(.099)	-.031	(.064)	.103	(.082)	.064†	(.039)
Female, < 6 years old	.090	(.094)	.064	(.045)	.144	(.107)	-.003	(.048)	.208**	(.086)	.071	(.062)
Male, > 60 years old	.244	(.190)	.047	(.092)	-.401†	(.255)	-.207†	(.134)	-.433**	(.204)	-.097	(.146)
Male, 16–60 years old	-.009	(.082)	.034	(.031)	-.359***	(.079)	.043	(.091)	-.077	(.081)	.044	(.032)
Male, 6–15 years old	.015	(.102)	-.076**	(.032)	-.031	(.097)	-.045	(.039)	-.064	(.085)	.083***	(.028)
Male, < 6 years old	-.122*	(.072)	-.094**	(.044)	.090	(.097)	-.028	(.040)	-.034	(.077)	.002	(.035)
Education	.171*	(.093)	.001	(.040)	.077	(.059)	-.053*	(.031)	.131**	(.063)	-.088**	(.040)
Durable asset (ln)	.042	(.045)	.004	(.018)	.066	(.050)	-.036**	(.018)	.054	(.048)	-.018	(.018)
Improved sanitation	.751	(.533)	.734***	(.282)	1.052*	(.549)	-.074	(.358)	.136	(.533)	.436*	(.238)
Finished floor	-.010	(.239)	-.209***	(.072)	-.043	(.193)	.039	(.070)	.015	(.193)	-.057	(.070)
Finished wall	.129	(.262)	.041	(.109)	-.222	(.317)	-.166	(.117)	-.609**	(.287)	.264†	(.172)
Improved water source	.596***	(.164)	.417***	(.161)	.654***	(.171)	-.003	(.143)	-.004	(.166)	-.064	(.062)
Garbage collection	-.583	(.472)	.135	(.207)	-.070	(.385)	.214	(.180)	-.148	(.384)	.436***	(.158)
Sewage system	-1.154**	(.536)	-.412	(.343)	-.726†	(.455)	.396†	(.247)	-.538	(.436)	.360*	(.197)
Own cow	-.089	(.466)	-.675***	(.138)	-.079	(.194)	-.058	(.072)	.761***	(.272)	-.756***	(.155)
Distance to food market	.072	(.072)	-.056*	(.029)	.035	(.041)	-.059***	(.020)	-.035	(.038)	-.013	(.017)
Altitude	-.003	(.002)	.000	(.001)	-.001	(.002)	.000	(.001)	-.002†	(.002)	.000	(.001)
Rainfall	.007*	(.004)	.000	(.002)	.007*	(.004)	.002	(.002)	.006†	(.004)	.002	(.002)
Distance to river	-.170	(.129)	-.205***	(.060)	-.183*	(.101)	-.037	(.055)	.178*	(.099)	-.135***	(.050)
Groundwater depth	.002	(.008)	.009***	(.003)	.020***	(.007)	-.002	(.005)	.006	(.006)	.000	(.002)
Ruggedness	.000	(.002)	.000	(.001)	.001	(.002)	.000	(.001)	-.005***	(.002)	.002*	(.001)
Obtained credit	-.128	(.290)	.013	(.145)	.307	(.312)	-.270*	(.142)	.428	(.326)	-.284*	(.168)
Area share of perennial crops (ln)	.226	(.358)	-.308**	(.126)	.297	(.272)	-.348***	(.124)	.023	(.218)	-.099	(.079)
Remittances received (ln)	-.072**	(.031)	-.067***	(.021)	-.003	(.024)	-.005	(.008)	.021	(.023)	-.035***	(.009)
Women's age	.000	(.009)			.586	(.533)			-.502	(.523)		
Women's education	-.011	(.041)			-.006	(.204)			-.020	(.184)		
Pregnant	.045	(.266)			.004	(.009)			-.001	(.009)		
Food price	.931*	(.566)			-.002	(.050)			.004	(.039)		
Own refrigerator, freezer	-.105	(.182)			-.327	(.279)			-.149	(.297)		
Inverse Mills ratio	-.703	(1.067)			.845	(.736)			-1.726***	(.562)		
Owned farm area (ln)			-.215***	(.059)			.722***	(.110)			-.560***	(.095)
Agricultural capital (ln)			-.020*	(.012)			-.021†	(.014)			-.007	(.011)
Intercept	Included		Included		Included		Included		Included		Included	
Effects of expected benefit on the adoption	.490** (.212)				.136 (.222)				.159 (.224)			
No. of obs.	2431		2431		1950		1950		2431		2431	

Source: Authors.

Note: LMB = Lee (1979), Maddala (1983), and Björklund and Moffitt (1987).

Asterisks indicate the statistical significance: †15%, *10%, **5%, ***1%.

Appendix A

Table 11. Production and imports of major food commodities in Tajikistan, 2007 and 2013

Commodity	2007			2013		
	Production	**Import**	**Domestic consumption**	**Production**	**Import**	**Domestic consumption**
	MT	**MT**	**MT**	**MT**	**MT**	**MT**
Barley and products	71,039	6,683	77,722	123,978	6,151	130,129
Maize and products	130,075	0	130,075	175,357	5	175,362
Rice (milled equivalent)	34,757	7,144	40,407	52,052	22,564	63,580
Wheat and products	649,300	947,759	1,596,280	947,350	957,620	1,969,354
Potatoes and products	662,093	25,900	686,693	1,115,700	45,280	1,160,953
Pulses, other, and products	16,878	1,002	17,802	48,061	1,308	49,339
Fruits (excluding wine)	274,134	20,085	178,342	503,835	1,689	384,234
Apples and products	111,000	18,264	57,574	227,000	1,009	131,117
Grapes and products (excl. wine)	116,934	70	91,800	175,335	100	170,628
Vegetables	1,089,270	5,127	888,864	1,985,900	8,016	1,876,510
Onions	217,000	20	119,136	413,300	1,965	312,576
Tomatoes and products	247,500	1,505	145,645	365,000	3,116	356,016
Vegetables, other	624,770	3,602	624,083	1,207,600	2,935	1,207,918
Oil crops	236,919	30	236,482	242,013	0	240,367
Vegetable oils	24,400	55,482	80,882	18,685	70,299	88,984
Pulses	24,652	5,316	29,890	63,549	5,063	68,582
Sugar and sweeteners	0	285,840	226,039	0	254,246	254,240

Source: FAO (2018).

Note: MT = metric tons.

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